LET’S TRACK!
STRATEGIES TO ESTABLISH ACTIVE PEOPLE TRACKING IN WORKPLACES

A dissertation submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy

MANI WILLIAMS
BE, MArch Melb

School of Architecture and Design
College of Design and Social Context
RMIT University

March, 2017
Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

Mani Williams
School of Architecture and Design
RMIT University
March, 2017
Credits

Portions of the material in this dissertation have previously appeared in the following publications:


- Mani Williams, Jane Burry, and Asha Rao (2015a). “Graph mining indoor tracking data for social interaction analysis”. In: Pervasive Computing and Communication Workshops (PerCom Workshops), 2015 IEEE International Conference on. IEEE, pp. 2–7


All trademarks are the property of their respective owners.
Acknowledgements

I would like to thank my supervisors, Professor Jane Burry and Professor Asha Rao for their continued support and positive encouragement throughout my candidature. Jane, your leadership and professionalism set the role model that I look up to for guidance and strive towards as a researcher. It has been such a pleasure and life learning experience working alongside you over the last four years.

This research was funded by the Australian Research Council’s (ARC) “Integrating architectural, mathematical and computing knowledge to capture the dynamics of air in design” funding scheme (project number DP130103228). The Chief Investigators were Professor Jane Burry, Professor Mark Burry, Professor Asha Rao, Professor Simon Watkins and Professor Robin Drogemuller (Queensland University of Technology). I would like to thank them and my fellow PhD candidates Daniel Prohasky, Philip Belesky and Sara Omrani for the continuous feedback during our regular ARC progress meetings. The ARC funding enabled me to acquire the equipment to build my prototype and travel internationally to conduct my case studies.

I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship. I am grateful for the financial support from RMIT University in the form of a scholarship and travel grants. My case studies benefited from the travel and project support contributed from SmartGeometry Organisation and Case Design Inc.. Travel and conference grants from Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) and Association for Computer Aided Design in Architecture (ACADIA) allowed me to both travel wider and network wider.

My case studies would not have been feasible without the support of the host organisations and my participants, specifically:

**Discovery** The participation of the students and staff of the Sense and Sustainability Workshop, and Professor Karin Hofert and the Polytechnic University of Catalonia for hosting.

**Exploration** Participants of the 2014 SmartGeometry Workshop and Shane Burger of
the SmartGeometry organisation. The host Professor Marc Aurel Schnabel and Chinese University of Hong Kong.

**Deployment** Case Design Inc. and their staff for the permission to study them in their work environment, and Daniel Davis and Andy Payne for the collaborative partnership.

My candidature benefited greatly from the RMIT School of Architecture and Design’s biannual Practice Research Symposiums (PRS). To my panellists, thank you for the wonderful insights. I would especially like to thank Professor Christopher Leckie (University of Melbourne) for the ongoing interest in and feedback of my research.

A number of people have provided invaluable advice over the course of my PhD. Flora Salim, Alexander Peña de Leon, Jessica Liebig and Weixin Huang: discussions with you have inspired me to develop new approaches and methods.

The Spatial Information Architecture Laboratory (SIAL) is and always will be a special place for me. Under the charismatic leadership of Jane, I was spoiled for choice to participate in the never-ending possible collaborative projects and draw on SIAL’s large professional network of alumni and industry partners. My close comradeship with fellow SIAL colleagues made the journey to a seemingly distant target a delightful journey. Rafael and Mehrnoush, I can report that the hours we spent chatting and the long lunches were always followed by a burst of sustained productivity.

Thank you my supportive friends Suleiman, Han, Yiwen, Ari and Derek for proof-reading.

To my husband Nathan and our son Alexander, your unconditional love and support carried me through all the highs and lows. Let us celebrate with cake; Alexander you can have all of the strawberries on the top.
to Nainai
Contents

1. Abstract 1

2. Introduction 3
   2.1. Background .................................................. 3

3. Literature Review 9
   3.1. Research Methodology ....................................... 9
   3.2. Data Collection ............................................... 12
   3.3. Analysis ....................................................... 14
   3.4. Applications of People Tracking ............................ 17
   3.5. Summary ...................................................... 19

4. Methodology 20
   4.1. Action Research Methodology ................................. 20
       4.1.1. Case Study Research Method .............................. 20
       4.1.2. Participant Observation .................................. 22
       4.1.3. Reflective Practice ...................................... 23
   4.2. Case Study Design ............................................ 25
       4.2.1. Preparation Stage ......................................... 28
       4.2.2. Fieldwork .................................................. 30
       4.2.3. Analysis ................................................... 31
   4.3. Methods of Evaluation ....................................... 36
       4.3.1. Hardware .................................................. 37
       4.3.2. Deployment ................................................ 38
   4.4. What’s Next .................................................... 40

5. Introducing the Case Studies 41

6. Case Study 1: Discovery 43
   6.1. Motivation ...................................................... 43
## Contents

### 6.2. Equipment Selection ............................ 43
### 6.3. Evaluation ...................................... 46
#### 6.3.1. People ...................................... 46
#### 6.3.2. Technology ................................. 51
#### 6.3.3. Analysis .................................... 56
### 6.4. In Reflection .................................... 67
### 6.5. What’s Next .................................... 68
### 6.6. Summary ........................................ 68

### 7. Case Study 2: Exploration ......................... 69
#### 7.1. Motivation ..................................... 69
#### 7.2. Graphical Representations of Theoretical Concepts .... 72
##### 7.2.1. Constructing Social Networks from Interpersonal Interactions ... 72
##### 7.2.2. Group Behaviours .......................... 77
##### 7.2.3. Building the Narrative ..................... 77
#### 7.3. Evaluation .................................... 81
##### 7.3.1. Adaptive Behaviour Modelling ................ 82
##### 7.3.2. Incorporating Context at Multiple Network Dimensions .......... 82
#### 7.4. In Reflection .................................... 85
#### 7.5. What’s Next .................................... 88
#### 7.6. Summary ........................................ 90

### 8. Case Study 3: Deployment .......................... 91
#### 8.1. Motivation ..................................... 91
#### 8.2. Setting Up for Success .......................... 93
##### 8.2.1. Building the Foundations ..................... 94
##### 8.2.2. Participant Engagement ....................... 94
##### 8.2.3. Targeted People Analytics .................... 95
#### 8.3. Evaluation .................................... 96
##### 8.3.1. The Set Up .................................. 96
##### 8.3.2. Analytics .................................... 98
##### 8.3.3. Participant Engagement Strategy ................ 101
#### 8.4. In Reflection .................................... 110
#### 8.5. What’s Next .................................... 112
#### 8.6. Summary ........................................ 114
Contents

9. Discussion 115
   9.1. A Holistic People-Centric Approach .............................................. 117
      9.1.1. Challenges ................................................................. 117
      9.1.2. Benefits ................................................................. 120
   9.2. An Analytic Grounded in Context: The insider insight ...................... 121
   9.3. Spotlight on Ethics .................................................................... 122
      9.3.1. Handling Consent and Data Collection in Shared Spaces .......... 123
      9.3.2. Tracking in the Workplace .............................................. 124
   9.4. Summary .............................................................................. 125

10. Conclusion 127

A. Published papers 129
   A.1. A multimodal toolkit for thermal performance feedback in conceptual
design modelling ................................................................. 129
   A.2. Applying social network analysis to design process research, a case study . 140
   A.3. Understanding social behaviors in the indoor environment: A complex
network approach .............................................................. 151
   A.4. A system for tracking and visualizing social interactions in a collaborative
work environment ............................................................. 178
   A.5. Graph mining indoor tracking data for social interaction analysis ...... 183
   A.6. Understanding face to face interactions in a collaborative setting: Methods and applications ........................................ 190

B. Unpublished Writings 211
   B.1. Visualizing Dynamic Bipartite Network with Spatial Attributes: a Force-
Directed Approach ............................................................. 211

C. Ethics Documentation Templates 219
   C.1. Plan Language Statement to Participants ....................................... 219
   C.2. Consent Form for Wearable Sensor Tracking .................................... 225
   C.3. Organisation Agreement .......................................................... 226

D. Letters of Ethics Approval from RMIT University 227
   D.1. Ethics Approval for the Discovery Case Study ............................... 228
   D.2. Ethics Approval for the Exploration Case Study ............................ 229
   D.3. Ethics Approval for the Deployment Case Study ........................... 230
List of Figures

1. Literature map ......................................................... 10
2. Methodology .......................................................... 21
3. Three case studies ..................................................... 26
4. People tracking system ............................................... 26
5. Timeline .............................................................. 29
6. Behaviour modelling ................................................. 32
7. *Discovery* Context .................................................. 44
8. *Discovery* IPMS version 1.0 ....................................... 47
9. *Discovery* Temporal plot ......................................... 52
10. *Discovery* Floor plan ............................................... 53
11. *Discovery* ZigBee tracking system performance testing .... 55
12. *Discovery* Data smoothing ........................................ 55
13. *Discovery* Movement simulation of the tracking data ....... 59
14. *Discovery* SNA temporal view ................................... 60
15. *Discovery* SNA overview ......................................... 61
16. *Discovery* SNA spatial view and heat maps .................... 62
17. *Discovery* SNA combined view examples ....................... 63
18. *Exploration* Context .............................................. 70
19. *Exploration* Proximity variations between the projects .... 73
20. *Exploration* IPMS version 2.0 .................................... 74
22. *Exploration* Interaction network with SNA .................... 76
23. *Exploration* Inner group dynamics .............................. 78
24. *Exploration* Highlighting out-reach interactions ............. 78
25. *Exploration* Pie chart comparing the proportion of in-group and out-group activities ........................................... 84
26. *Exploration* Organisational-wide interaction dynamics .... 86
27. *Exploration* Interaction dynamics seen in heat maps ....... 87
28. *Exploration* Organiser’s reach .................................. 89
## List of Figures

29.  *Deployment* Context ........................................... 92
30.  *Deployment* Visualising locations .............................. 99
31.  *Deployment* People’s latest movements ....................... 99
32.  *Deployment* Proximity density example ....................... 103
33.  *Deployment* Departmental activeness level .................. 104
34.  *Deployment* Social interaction network ....................... 105
35.  *Deployment* Social interaction network per group .......... 106
36.  *Deployment* Movement triggered interactions ............... 106
37.  *Deployment* Project network evolution ........................ 111
38.  *Deployment* Project network analysed ........................ 113
39.  *Deployment* Space usage analytics developed by the host .... 113
40.  Strategies to establish active people tracking ............... 116
## List of Supplementary Figures

1. *Discovery* Group-location measures ........................................ 57
2. *Discovery* Coordinator’s queries ........................................... 65
3. *Discovery* Project leader’s queries ....................................... 66
4. *Exploration* Spatial interaction maps ..................................... 79
5. *Exploration* Photo evidence ................................................ 80
6. *Exploration* Spatial interaction map of FBR .............................. 80
7. *Deployment* Active rank plot ............................................... 102
8. *Deployment* The *Gang War* tactics ...................................... 108
### Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
<th>Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLE</td>
<td>Bluetooth low energy. 93, 94, 97, 101, 112</td>
<td></td>
</tr>
<tr>
<td>DSINM</td>
<td>Dynamic Social Interaction Network Model. 30, 100, 110, 112, 127</td>
<td></td>
</tr>
<tr>
<td>ERP</td>
<td>enterprise resource planning. 17, 93, 95, 97, 111, 112, 119</td>
<td></td>
</tr>
<tr>
<td>FDL</td>
<td>force direct layout. 16, 72, 75, 82</td>
<td></td>
</tr>
<tr>
<td>ID</td>
<td>identification. 34, 82, 96, 98</td>
<td></td>
</tr>
<tr>
<td>IP</td>
<td>intellectual property. 97, 219</td>
<td></td>
</tr>
<tr>
<td>IPMS</td>
<td>indoor people monitoring system. 23, 28, 46, 47, 68, 69, 72, 74, 85, 88, 90, 93, 98, 112, 127</td>
<td></td>
</tr>
<tr>
<td>NPD</td>
<td>new product design. 18</td>
<td></td>
</tr>
<tr>
<td>PAR</td>
<td>participatory action research. 5, 23, 37, 127</td>
<td></td>
</tr>
<tr>
<td>RFID</td>
<td>Radio Frequency Identification. 13</td>
<td></td>
</tr>
<tr>
<td>RSSI</td>
<td>received signal strength indicator. 48, 54, 74, 82</td>
<td></td>
</tr>
<tr>
<td>SIAL</td>
<td>Spatial Information Architecture Laboratory. 5, 41, 91</td>
<td></td>
</tr>
<tr>
<td>SNA</td>
<td>social network analysis. 14–16, 33, 34, 43, 56, 72, 82, 121</td>
<td></td>
</tr>
<tr>
<td>SQL</td>
<td>Structured Query Language. 51, 67</td>
<td></td>
</tr>
<tr>
<td>WSN</td>
<td>wireless sensor network. 12, 46, 48, 54, 68, 82</td>
<td></td>
</tr>
</tbody>
</table>
1. Abstract

This research presents a user-centric approach to establish active people tracking in workplaces.

With advanced tracking technologies becoming accessible, more businesses and organisations are tempted to experiment with the new trend of people tracking for management and planning purposes. Which system to use, what to do with the data and how to get the staff on board are common questions that the managements have little experience and precedence to look up. These questions point to fundamental issues in adapting data-driven people analytics in the workplace. My research addresses these questions with three targeted, real world case studies; each focusing on one of these issues.

The status quo of a top-down authoritarian workplace management approach that focuses only on providing feedback to management is assumed by academia and industry. This hinders the deployment of individual-targeted practices such as people tracking, which people perceive as intrusive and impeding. This has unfortunately obstructed many state-of-the-art technologies and processes from benefiting the wider public. This motivated me to explore strategies to make academic research accessible and technologies more approachable. My goal was to reach out to individuals from all levels of the organisation and provide all stakeholders with access to analytical insights.

I achieved this through utilising the participatory action research methodology. I embraced real world case studies to reveal the practical issues organisations would face in the process from planning people tracking to adapting it into their daily operations. Within each case study I practised participant observation to access multiple stakeholders’ points of view. I set out to discover the relevant insights that are important for different stakeholders.

The action research component is conducted by developing a system that delivers insights into teamwork dynamics, as revealed by tracking the social network interactions that occur within collaborative work environments. I constructed a working prototype that utilised an indoor people tracking system that captures people’s movements as they operate within their workspace. It is capable of simultaneously monitoring the progress of multiple cohabitating project teams. Focusing on providing context specific insights,
1. Abstract

I designed a flexible behaviour model that constructed customised social networks to extract interactions of interest from the tracked data. The visually rich analysis reporting that was layered with contextual cues enabled quick cognition by the intended viewer. The targeted user covers all levels of the organisation from project collaborators to the support personnel and upper management. With this setup, everyone can participate in a data-supported reflective learning process.

The original contribution of my research is two-fold. Firstly, the people tracking system and analytics I developed demonstrated the technical capability to provide real time insights to workspace design, project management and human resource management applications. Secondly, through reference to my three case studies, I argue that a user-centric approach is critical for the successful integration and adaptation of people tracking systems and analytics into real world workplace practices.
2. Introduction

This thesis is on social interaction in workplaces. In the context of this thesis the definition of workplace is *place of work* (compare to a place for leisure or rest). Using this definition, places that employees conducted paid work, the spaces used by students to study, the work spaces workshop participants used to interact with each other and fabricate models were all considered as “workplace”.

My research set out to explore ways to inform face-to-face interactions in workplaces with data-driven insights. To complete this quest, there are many hurdles to cross such as: what data would be useful, how to collect the data, and how to process and present the data in an informative way. These questions were interconnected like a web, with a decision made in one aspect to have a significant impact on others. Part of my research was to achieve a balance that is practical for applying in the real world.

I have decided to take a narrative approach in writing up this dissertation document. I have strung together my major case studies with in-depth reflection of preparation, execution and lessons learnt from each. This way, I highlight the iterative nature through which my holistic user-centric approach was conceived and developed upon. Much of the technical details have been published in peer-reviewed papers. Referencing a document structure more common in a *PhD by Publication* thesis, I have included summaries and extracts of the papers when needed and direct the reader to the appendices where the full papers and other technical documentations are attached. This way, I aim to maintain a narrative tone in the subsequent chapters.

2.1. Background

Here is a brief introduction of my background and how it led to this topic, as this is not a project given to me, but one that I formed by myself, something that has personal motivation and deep personal interest.

My research is multidisciplinary in nature. It has been hard at the onset working out how I should approach it, as there is no clear research methodology for me to follow. I am situated in the School of Architecture and Design of RMIT University, where we were
2. Introduction

encouraged to “self-reflect while doing”. I have also found that my research question -
the quest - evolved in the process, slowly becoming clear what I was actually discovering.
It was intimidating and uncomfortable at the beginning, since I came from a science and
engineering background where there is a universally expected process for conducting
and reporting research. Heading into architecture and design, I arrived at the opposite
end of the spectrum where there is no guideline, no goal post. I was encouraged to
explore the work but also to express (present) the work. It was not until I was one
year in that I became confident in myself. I came to appreciate the multidisciplinary
nature of my work. The liberty is something to be celebrated, not confining to one
existing methodology but to explore the best of many. My process has been a journey
of self-discovery, which I now will present to you.

Throughout the journey, I ventured out into many fields of research in search of inspira-
tion and comparison. Being engineer trained, I am a practical person. My approach
is “it can be quick and dirty but it has to work”. So I was surprised at the notion of
“(design) concepts”: running away with the idea or the proposal, and the finer detail
can come later (and sorted out by other people, most likely engineers). I was and still
am fascinated by how people in the design profession became easily excited about ideas
that seem to be the norm in other fields. At the beginning, I thought designers are
constantly reinventing the wheel, but now I am impressed by how designers are able
to discover new applications, repurpose existing tools and ultimately introduce ideas to
the masses. In this candidature, I struck a balance between my practical self and my
discovery self to present a working prototype of a concept that is aimed for large-scale
implementation that I have tested in several case studies.

My motivation for the thesis topic itself came from my own experience in collaborative
team projects. The frustration in the process came from misalignment in how different
people approach the project, unfamiliarity in my team members (“can I trust them?”)
and the out of control feeling of “what if they don’t deliver, how will it affect the overall
delivery”. Despite these shortcomings, I kept signing up for more because I enjoy the
thrill of the unknown, the surprise of what others can bring to the table, and how the
whole is greater than the sum of the few. I wish my research can assist future projects
in developing trust, maintain control, and at the same time maximise the contribution
of each team member.

One collaborative project experience had been in the forefront of my mind throughout
my candidature. It was my participation in the SmartGeometry 2013 event, a four-day
long intensive design workshop. I was part of a group of researchers that developed the
material for one of the ten workshops. Our brief was to develop a system for evaluating
2. Introduction

the thermal performance of facades, package it in Melbourne, Australia and fly it with the team to London, UK. A dozen workshop participants joined us for the four days to develop and test their designs using our system. Throughout this project, from workshop development to the workshop event, I experienced all of the emotions I mentioned above: frustration of the uncertainty, project progress out of control, amazement at the outcomes and surprise contributions from team members.

Tools and platforms exist to help people manage the tangible artefacts and the work that has been produced. Managing the intangible, such as the project progress and people relationships, seems to be a skill that improves with experience. It was especially hard, when I was trying to do my part of the project, to spare a thought for what was going on around me. It seemed that what I needed was a “God’s eye” view to oversee the whole operation, something that gave me a quick insight when I needed, to let me know who or where I could go to seek more information. This conceived the pilot Discovery project of the thesis.

There are many different approaches to constructing a system that can report on the atmosphere of collaborations. I decided to tackle it by tracking people’s behaviour, specifically their interactions with each other. My hypothesis is that by informing the project team of how the team members interact with each other, the leader would be able to know whether the team relationship is healthy and make informed project management decisions. Moreover, if this information is made available to the team members, they could be more aware of other people as well as the progress of the project, which could help build trust with each other and remove some stress from uncertainties.

As part of the Spatial Information Architecture Laboratory (SIAL) at RMIT University, an active research laboratory that is world renowned for its wide network of contacts and the breadth of its multidisciplinary projects, I had access to a vast number of past, current and in-planning collaboration projects, and was encouraged to participate in them. The projects varied in duration and context, some were in the tertiary education context, others were collaborations with the professional industry with many a combination of the two. I jumped at the chance to utilise these opportunities at my disposal, and it lent itself to the participatory action research (PAR) approach. I was fortunate to be able to cherry-pick and participate in appropriate projects that suited my research agenda.

People interaction has been fascinating to researchers for a long time. One of the most famous papers in sociology is “The strength of weak ties: A network theory revisited” (Granovetter 1983), in which the author argued the importance of maintaining social relations with a wide range of contacts and familiarities. The well known “The small
world problem” (Travers and Milgram 1967) described how the world is really much closer to us through our network of friends of friends. Looking behind the cliché, I discovered that these research claims are based on small data sets collected using simple data techniques of surveys and questionnaires. It is a demonstration of the brilliance of the researchers to make such ground-breaking conclusions from such data. Fast forward many decades to now, I was surprised to find that questionnaires and interviews are still the leading data collection techniques utilised by social and behavioural researchers (Johnson and Turner 2003). Questionnaires are limited in the data they are collecting; interviews offer more freedom but are slow and laborious to process, and data records are recollection-based thus subjective and inaccurate.

With the rise of the Big Data era, designers and engineers are increasingly interested in exploring social data mining applications of data collected from digital devices, revealing many social implications in the process (Boyd and Crawford 2012). We are surrounded by data-generating devices and systems that are constantly reporting traces of our movements and behaviour. People are in two minds. It is tempting to embrace this cultural revolution but we should be equally wary of its unforeseen consequences. For example, “google it” is second nature for many, but Google is able to deduce so much personal information from our searches as to bombard us with targeted advertising (Google 2017).

One of the most frequently asked questions I received from my research participants is: “How is the data collected from me going to impact me?” The care of the participants is one of the ethos of research ethics. It is especially difficult in the context of people interaction research as the sample size is typically not large enough to offer participants protection by anonymity in numbers and the validation of our research is based on people truthfully reporting identifiable data (Borgatti and Molina 2003). Many researchers get around this issue by removing participants from a real world context and constructing a controlled scenario where the rules of observation and engagement were clearly defined (Falk and Heckman 2009). In the design discipline, the use of protocol analysis research methods has becoming increasing popular (Jiang and Yen 2009). This approach has a clear flaw in that it is hard to argue the generality of these research findings in a real world context, not to mention the difficulty of scaling to different participant sample sizes and experiment durations.

A case study approach bridges social interaction research with industry workplace applications, as shown in Boutellier et al. (Boutellier et al. 2008). A case study that collects a context-relevant dataset in an ethical and sustainable manner can provide real world data to theoretical researchers and the data-based insights to professional practice (Borgatti and Molina 2003). This is a win-win scenario that benefits all parties
2. Introduction

involved and will promote wider collaboration and adaptation. This is the rationale of the research presented here.

One aspect of my research is to develop a data collection system that is applicable in the real world and responds to the needs of participants. The criteria for such a system were:

**Independent** – The operation of the system should be not overly reliant on existing infrastructure; the physical system must be able to be packed and transported.

**Scalable** – The application of the system must be suitable to a range of contexts and data collection scenarios.

**Beneficial** – The deployment of the system should minimise intrusion to participants’ daily routine, entice participation through insight sharing, and foster a sense of ownership in the data.

I prepared an indoor tracking system and wearable tracking tags to collect location data from people. The system is self contained: tracking beacons and tags communicate on the independent ZigBee mesh network, data collected is stored on a local database hosted on a RaspberryPi computer and backed up in a cloud server, which also handles the automated data analytic scripts to provide live analysis. Physically, the whole system packed into a suitcase that travelled with me to my international case studies. The configuration of the system was flexible, configurations of the stationary tracking beacons could be determined on-site and adapted throughout the data collection process. Low cost battery powered tracking tags are scalable and simplified the participant signup process. Participant management was handled with the high-level data mining. The fact that the tags could be worn or put aside, allowed participants to have more control of when they wished to be recorded.

I have selected three different people collaboration settings as my case studies. The case studies were all real world scenarios, the first was a short design studio class, the second was an intensive international design workshop, the third was few weeks in a design consulting office. With each case study, I practiced in-depth participant observation where I submerged myself in actual collaboration project work as an active team member. This allowed me to observe the people interactions as an insider and build rapport with the participants. The brief for data analytics was based on input from the case study participants and my personal experience, as this offers validation of the list of insights for people in similar scenarios. The participant engagement strategy I prepared as part of the case study is also an essential part of my research. A positive participant engagement and focus on providing insights back to the participants is a major success factor for my case study research methodology. My case studies demonstrate a work-
2. Introduction

In this document I will present my case studies, which focus on development of context-specific people interaction analytics based on indoor people tracking data. Referring to the case studies, I will discuss my approaches in preparing case studies and reflect on the strategies of case study management. I will conclude my dissertation with detailed recommendations on how to conduct people interaction research in workplace environments and similar contexts.
3. Literature Review

The work presented here sits at the intersection of many disciplines (Figure 1).

3.1. Research Methodology

The context that I chose to study is collaboration in the architecture and design discipline. Design Studies is a field of research that is interested in the process of design (Cross 1982). The popular protocol analysis approach to studying collaborative design process has been deconstructing the collaboration process into small design decisions, categorising into set types, identifying how each decision contributed to the exploration and development of a design concept (Gero and McNeill 1998). One aspect of the design studies research is face-to-face collaboration in the form of how each person contributes to the exploration and development of a design concept. Design study research has been predominately conducted under simulated conditions, where participants were put in an experiment set up and given short design tasks to complete under observation (Jiang and Yen 2009).

One well known set up was the subject of the 1994 Delft Protocol Analysis workshop (Cross, Dorst, and Christiaans 1996). A selected group of design researchers attended the workshop to explore protocol analysis on the two sets of data (Dorst 1995). The data were videotapes and transcriptions of the process of a single person and a group of three designers working on a simple design task for two hours. It popularised protocol analysis (along with survey instruments, input-output experiments and fMIR based studies) as a research method for investigating design cognition (Gero 2010). Unlike the fMIR and input-out experiments, in principle it is possible to apply protocol analysis to real life design discussions. However the large resources required to fully capture, transcribe and analyse a design process using protocol analysis meant that it is mostly applied to design discussions that are 20 minutes to 2 hours in duration (Jiang and Yen 2009). For longer process surveys instruments (such as questionnaires and interviews) were used for data collection. Linkograph (Goldschmidt 1990; Goldschmidt 2014; Kvan and Gao 2006) is a method of analysing a design progress both quantitatively (through measures
3. Literature Review

Figure 1.: The work presented here sits at the intersection of many disciplines. This mind map shows how components of this thesis referenced different discipline fields, with the solid lines indicated where my research also made original contributions.
3. Literature Review

such as “links per move”) and qualitatively (visualising the link and moves as a network to demonstrate different design behaviours such as “chunks” and “webs”). Protocol analysis coupled with linkograph offer good insights on the design process but they are resource intensive to conduct for a full-length project.

At the turn of the century, with the wide adaptation of computer-aided tools (such as CAD software and BIM systems) in the design industry, the academic field shifted its focus to study design processes that are mediated by computer tools (Kvan 1994; Burry and Burrow 2005; Richens 1994; Soufi and Edmonds 1996; Williams et al. 2013) as well as virtual interactions conducted with synchronised (Kvan 2001; Kan and Gero 2008; Bender 2005) or asynchronous collaborations (Burrow and Burry 2006; Karakaya and Şenyapılı 2008; Leenders, Van Engelen, and Kratzer 2003). By running monitoring software to capture people’s computer inputs, design study researchers could now utilise automated means of capturing data on the design process (Laat et al. 2007). It appears that research has been sidetracked with the development of new and exciting methods to capture people’s design inputs, that we have stalled on exploring how to apply the research to real world scenarios. For the research in design studies to have a greater impact it needs to be demonstrated with industry based studies. There are many hurdles in applying the above-mentioned methods beyond experimental design setups to real life profit-driven projects (Halverson 2002; Grudin 1988; Martínez-Moné, Harrer, and Dimitriadis 2011). This unfortunately diminishes the credibility of the research claims and hinders the potential impact of design research in general.

A different approach came from social science, in which area researchers are studying the cognitive process of creativity. In contrast to design studies, in this field cognitive researchers were more interested in how people do things, rather than what they have done. For example they look at whether people are more creative in groups or work better individually (Paulus and Brown 2007; Johnson and Carruthers 2006; Woolley et al. 2010), whether social bonding improves team performance (Johnson and Carruthers 2006; Hu and Liden 2015; Google 2015) and compares the different organisational structures (Shore, Bernstein, and Lazer 2015; Burt 2004). They too conduct research in controlled experiment settings, but the research findings are presented as simple practical recommendations for the real world. Those recommendations were tested in real world practice by researchers in organisational studies (Newell, Tansley, and Huang 2004), whose research strategy is to collaborate with business operation and management departments in large industry organisations (Ehrlich, Lin, and Griffiths-Fisher 2007; Kirkham et al. 2013). They link actionable academic theories to measurable impacts on the organisations (staff productivity, and ultimately, monetary profit) (Boutellier et al.
3. Literature Review

One issue I have with the approach taken by the social scientists is that the studies’ identified benefits lie with the top management level and the evaluation is mostly monetary in terms of increase in productivity value, a capitalist authoritarian approach that does not consider the people of the organisation as individuals. I am a believer in the design discipline’s reflective practitioner approach: encouraging the learning process through feedback and reflection, celebrating creativity in individuality and in the external experience that each individual brings to the table, acknowledging the contribution and the effect of the context in decision making. That said I believe there is much to be learned from the practice-based research methods. This allows me to be one step closer to having my research accepted and adapted into practice, which is a fundamental motivation of my work.

3.2. Data Collection

One aspect that can help ethnographical research is access to ongoing data. Limited by the labour-intensive data collection and categorisation process, current workplace researchers typically work with data collected during infrequent day-time visits. It is known that people behave differently when they are observed (Monahan and Fisher 2010). In terms of the operations carried out in those offices they were snapshots and can hardly provide a picture of the dynamics of the people and office. Reflective practice (Schön 1984) and participant observation (Spradley and McCurdy 1980) are two methodologies for long-term ethnography studies. They are excellent for collecting process data when used consistently; this is difficult to achieve in practice unless it is integrated into the main design documentation process. I explored this through analysing design project meeting notes to study project development dynamics (Williams, Burry, and Rao 2014a, A.2).

I looked further afield for alternative ways to collect data that was suitable for long-term in situ observations. Works in ubiquitous computing (UbiComp) and wireless sensor network (WSN) provided precedence (Gu, Lo, and Niemegeers 2009; Microsoft 2016)). I focused on systems that can identify and track individuals. Camera-based systems running feature recognition algorithms in theory allowed for more capacity and flexibility, but as they require line of sight to body and/or face to operate, many cameras are needed to cover the area to track individuals as they move about. Limited device mounting options restrict data quality, and the advance algorithms required to compensate as well as effectively handle camera-to-camera transition make it an expensive system overall.
3. Literature Review

Wearable tracking systems offered a simpler and stabler alternative as the system typically adapts established wireless communication network standard to perform object identification and tracking. Liu et al. (2007) provided an overview of technologies that can provide indoor positioning data and applications that use these data. Smith et al. (2013) utilised a Radio Frequency Identification (RFID) system to provide people movement data for a study on activity level at work. Biczók et al. (2014) constructed MazeMap, an indoor navigation service for students and staff on campus that uses the university’s WiFi network to locate people by their personal devices. Ruiz-Ruiz et al. (2014) demonstrated the rich insights provided by WiFi-based people tracking for building facility planning application in a hospital. Yoshimura et al. (2014) studied museum visitors’ movement path using data collected by Bluetooth proximity sensors.

In indoor tracking applications, typically the space is installed with fixed “beacons” that acts as reference points, mobile “tags” are carried by the people. Once a person carrying a tag enters into the signal reception area of a beacon, a “hand-shake” occurs between the beacon and tag, and the tag is registered within the network. As the tags move between the reception areas of different beacons, we are able to proximate the location of the tag by the difference in signal strength it receives from the close by beacons. I have constructed my data collection system based on an off the shelf ZigBee-based indoor tracking system and a cloud database. Unlike WiFi or Bluetooth based personal device tracking systems, the ZigBee system is a self-contained system that neither require operators to have detailed knowledge of existing infrastructure nor require access to personal devices.

The accuracy of positioning a person within indoor spaces is limited due to the complex nature of the environments where the presence of furniture and movement of people distorts the wireless signal paths. Improving indoor positioning accuracy is an active area of research, with researchers tackling it at both the device level and the system level (Koyuncu and Yang 2010).

If the focus is on analysing social links/interactions then it may be possible to relax the spatial accuracy requirement and to compensate with a larger time sample (Dong, Lepri, and Pentland 2011). Link mining, a branch of the field of data mining, is a method that extracts identities and builds associations from large datasets. Eagle and Pentland (2006) built social patterns based on tracking personal devices. Outside human interactions applications from livestock management research offer precedence in data modelling and analysis (Guo et al. 2006; Handcock et al. 2009; Böhm, Hutchings, and White 2009). I explored two link mining approaches to extract people interaction data from my tracking dataset (Williams, Burry, and Rao 2015a, A.5). The two methods
3. Literature Review

took different approaches in interpreting beacon-tag tracking data into people-to-people interaction events. In the paper I discussed how the choice between the two methods depended on the physical sensor set up, the predictability of social events and how by manipulating the algorithm parameters the methods can be tuned to extract different types of interactions.

3.3. Analysis

Once we had a data collection system that supplies us with ongoing data and methods to extract associations that link people to each other, this lent itself to be represented as social networks. A network, in its simplest form, is a collection of discrete nodes joined by pair-wise links. Originating in mathematical graph theory, the study and application of network theory has quickly grown into an interdisciplinary field with inputs from physics, biology, computer science, social science and other areas. Through a network approach, researchers are able to reduce complex natural phenomena into an abstract form for further analysis of component dependencies and the formation of structural identities. social network analysis (SNA) is a branch of network science that focuses on developing methods to understand network data that represents social interactions.

Design science’s linkograph is an application of SNA. Many of Linkograph’s qualitative analysis methods can be translated and supported with similar SNA methods: Design moves and their links forms a (directed) network, “chunks” are sub-networks that can be identified by community detection, “webs” are nodes with high clustering coefficient. Additional SNA methods such as network node centrality measures were also insightful for the study of design processes (Williams, Burry, and Rao 2014a, A.2).

The social network model allowed researchers to study the data from multiple scales (Wasserman and Faust 1994). From top down there are global network measures such as network density, global clustering coefficient and network work visualisation force field layouts that provide the holistic representation of the captured behaviour. From the inside there are egocentric measures such as local clustering coefficient and centrality measures that give insights into the behaviour of the individual in relation to the whole. In between the two ends of the spectrum there is also community detection to study the structure and segregation of the network. In the areas of built environments and construction, Chinowsky, Diekmann, and Galotti (2008) put forward several SNA models that can be applied to engineering and construction projects, representing a range of interconnections including project composition and communication, and demonstrated the potential of SNA to improve team performance. Korkmaz and Singh (2012) observed
collaborative interactions of two groups of architecture, engineering and construction students which confirmed that a SNA model was able to reveal insight on team dynamics and performance.

I studied how an existing group of people behaved amongst a larger organisation. Batallas and Yassine (2006) modelled team communications within a large commercial product development project and by using network characteristics they able to reveal teams that held strategic positions in the information exchange network that could be better utilised. In People Analytics: How Social Sensing Technology Will Transform Business and What It Tells Us About the Future of Work (2013, p158) Ben Waber described that, by monitoring integrations between team members using wearable sensors, he was able to observe the change in communication pattern as a group of strangers settle into a team relationship. In a separate study he found that the transition between a diverse interaction network to a cohesive one indicated a shift in team development stage: a diverse network supports exploration and a cohesive network works better for the development stage. Waber draws comparison with the “The strength of weak ties: A network theory revisited” that diverse connections open up opportunities. In Social Physics: How Good Ideas Spread (2014, p89) Alex Pentland identified “exploration” (interactions between different teams) and “engagement” (interactions within a team) as two team-based behaviours that affect productivity and creativity. Both Waber and Pentland are in agreement that a cohesive team interaction network is more productive. Pentland showed that within an organisation matching their face-to-face interdepartmental exploration with their interdepartmental virtual communications improves the organisation’s coordination (Pentland 2014, p100). Both studies step short of giving recommendations on the quantity of interactions, instead suggesting a “balance” (Waber 2013, p70) or “alternate between” (Pentland 2014, p97) the two to drive behaviour change. It is clear that both authors have found that 1) tracking social interaction network over time is insightful for management of decision making, and 2) decision to act on these insights should be made with consideration of the context. Inspired by these studies, I developed my interpretation of team-based exploration and engagement models.

Although there are dynamic network methods for quantitatively analysing networks that change over time (Boccaletti et al. 2006; Berger-Wolf and Saia 2006), I decided interpretation of these methods for my case studies was beyond the scope of this research. Instead I focus on exploring ways to visually present the dynamic nature of social interactions.

From my experience collaborating with SNA researchers on the case studies I found
that current data visualisation techniques used in network analysis in academia do not provide adequate support for non-network science specialists to draw insights. With designers as my case study participants, and targeted users, I avoided using performance matrices and texts to present data findings, instead focusing on presenting analysis results graphically for interpretation.

There are a range of open source and commercial tools available to develop and run automatic scripts that analyse the incoming data and display the results for their users. Extensive data visualisation libraries in analytical software packages such as R (R Core Team 2013) and MATLAB®, software plugin NodeXL (Smith et al. 2009) for Microsoft Excel™, packages for Python™ and the D3.js package (Bostock 2010) for JavaScript™ have made social network analysis more accessible to the public. Mark Huisman and Marijtje AJ van Duijn 2011 provided an extensive review of the SNA software and offered recommendations based on intended application. I chose to use the R language and the development platform RStudio (RStudio Team 2015) for my research. R is widely used by the statisticians and data mining scholars who has contributed open source libraries of well known analysis and visualisation algorithms and examples.

Classic texts such as The Visual Display of Quantitative Information (1986) by Edward R. Tufte and Semiology of Graphics (1983) by Jacques Bertin focused on effective visual communication of statistical data but they provided inspirations for designing graphical representation for networks. Network visualisation is typically a mapping exercise where a complex connected network of nodes and links are arranged in a 2-dimensional or 3-dimensional space so that certain information of the network is encoded in the structure layout and can be easily perceived by the viewer (Krempel 2011). Simple network node placements such as sphere or circular layout arrange the network nodes in a predetermined geometry. This is effective with small networks to show the distribution of the network links and is comparable between networks of similar node sizes.

Alternatively, force direct layout (FDL) algorithms (Fruchterman and Reingold 1991; Kamada and Kawai 1989) iterative compute the network node placement by interpreting the network structure as a physical system. This helps visual cognition of the overall network structure as the solution finding process places more connected nodes in the centre of the layout. The consequence is that these algorithms are resource intensive to compute, shortcuts are needed for very large networks. Also the solution finding is not deterministic thus the same network could generate layouts that have different node placements. It is hard to compare two networks drawn using FDL and make comments on individual nodes and links. Research in visual analytics and information visualisation
explored deeper engagement of viewer’s visual cognition of network data through methods such as multi layer data and animated data representations (Nesbitt and Friedrich 2002; Moody, McFarland, and Bender-deMoll 2005; Munzner 2009; Brandes, Indlekofer, and Mader 2012; Krzywinski et al. 2012). My case studies explored animated network visualisation as a method to convey behaviour dynamics of large longitudinal data.

Agent-based simulation also offered inspirations for visualising dynamic data (Kornhauser, Wilensky, and Rand 2009). Based on agent-based simulation, I have developed a transition view dynamic data visualisation method that was effective in visually communicate the movement of people as recorded by the sensors (Williams, Burry, and Rao 2014b). This method was used in the post data collection longitudinal analysis phase of the first two case studies, and adapted to live data visualisation for the third case study.

Looking afield, interactive data graphics offered with platforms such as D3.js (Bostock 2010) and Shiny (RStudio Team 2016) allowed additional data to be embedded in the visualisation, through dynamic rendering responding to user inputs such as click and drag, users interact with individual nodes and links to manipulate the network or unveil additional information. Presently, interactive data visualisation are mainly used in data reporting of small and refined dataset. To apply it to large tracking data set requires a well designed data preparation layer that sits between an interactive user interface and the tracking data. This was beyond the scope of this thesis, but my initial exploration using Shiny with R showed great potential to enrich the way that insights are communicated to the user and how they engage with tracking data.

3.4. Applications of People Tracking

In organisational management operations, remuneration and promotion decisions traditionally relied on enterprise resource planning (ERP) data, questionnaires, interviews and observations (Aguinis 2009). However Waber (2013, p29) claims that these do not encourage knowledge sharing and proposed to use wearable sensors to map the interaction network of the organisation in order to identify and reward experts and encourage knowledge sharing. Waber’s sociometric badge was able to identify the experts and the expert of experts in an IT firm which allow individual’s informal contributions to be recognised (Waber and Pentland 2009). I believe the findings from such a knowledge network should not only be used in remuneration and promotion decisions but provided to the employees and teams. This allows individuals to use this data to identify experts when needed, and also benefit from the feedback. Team leaders could also use this data. Leenders, Van Engelen, and Kratzer (2003) demonstrated that communication frequency
and centralisation affects collaborative creativity in new product design (NPD) teams. It was suggested that the design of a NPD team should focus on increasing team member proximity, support ad hoc communication and the application of task structuring.

There has been a growing interest in understanding social interactions in the spatial context (Koylu et al. 2013; Biczók et al. 2014; Stopczynski et al. 2013). Conceived in the first case study (Chapter 6) and expanded in the second case study (Chapter 7), I have tracked people’s face-to-face interactions and overlaying it with the locations that the meetings occurred in. It has provided deeper insights into why certain spaces are more popular, and whether the user pattern matched the design intentions. The third case study (Chapter 8) demonstrated how ongoing tracking and analysis can also provide tools for space managers to redesign and adapt spaces to the use over many iterations.

Space syntax is a research area that is interested in the configuration of inhabitable spaces (Bafna 2003). A network model is frequently used to represent space configurations, with the network nodes representing compartmentalised spaces and network links representing connections as perceived by its habitants (such as physical connection or line of sight). With increasing popularity of open-planned spaces this process of network generation is no longer straightforward. A beacon-tag sensor setup can offer an alternative way to construct spatial networks, as demonstrated in Williams, Burry, and Rao (2014b), as a part of my second case study.

Currently post occupancy evaluation practice is predominately focused on indoor environmental quality (Guerin et al. 2013). Ongoing people tracking could provide insight on people’s workstation preferences, especially with hot desk set ups, from which management can infer space usage efficiency. This data compared with the design brief can comment on the success of the office design and provide suggestions and live feedback on interventions. With wearable sensors we can identify data captured from an individual, allowing us to conduct focus analysis on subgroup of the occupants (for example, examining the different usage pattern of staff, undergraduate and postgraduate students).

Wireless communication services on personal devices already broadcast identifications that allows an individual’s location to be tracked as one moves about (Pan et al. 2013; Sapiezynski et al. 2015). Privacy and the ethics discussions are still coming to terms with this abundance of personal location data. Privacy laws protect individuals from being identified, but the practise of accumulated anonymised data falls into the grey area. It is shown that the use of pseudonyms does not offer sufficient protection of location privacy (Beresford and Stajano 2003; Demir, Cunche, and Lauradoux 2014). For the data collectors there is little incentive for them to restrain, but just because it is legal does not mean it is ethical (Helbing 2015). There is also the consideration that the data
collection through this wide net casting approach may not be representative of the population. Using WiFi-based tracking for example, without WiFi enabled devices people are invisible to WiFi sniffers, and people carrying multiple devices are over represented in the same system. I have chosen to use a stand alone wearable sensor system so that I have full control over the tracking components. This set up allowed my participants to have easy control over their participation: they simply remove the tracking tag when they need privacy.

Research examining people’s willingness to disclose their location found that the most important factors were who was requesting and the reason of the request, and the response rate was higher when the subject were in a positive mood (Consolvo et al. 2005). This indicated the importance of maintaining trust and rapport with my participants to achieve high level of data representation when using a system that supports flexible participation.

3.5. Summary

To summarise, positioned in the architecture and design discipline I identified the difficulties in applying design studies research to industry practices. I will cross discipline boundaries and seek precedence of automated data collection techniques and analytic methods. My contribution will be in the interpret and adapt multidisciplinary knowledge to real world contexts, focusing on developing user engagement and exploring the theory to practice integration process.
4. Methodology

4.1. Action Research Methodology

I utilised the action research methodology (Lewin 1946; Susman and Evered 1978) to iteratively explore my research in three different settings. Action research is the process of learning through doing. With action research, not only is the end unknown, but the journey too.

It is suitable for practice-based research in which the applicability of the research proposal is tested in situ. It is a research approach that is supported by the PhD by project program at RMIT University’s School of Architecture Design (Glanville and van Schaik 2003; Blythe and van Schaik 2013). Practice-based action research allows the real world to come into play, shake up the ideal situation that the proposal was developed in and bring to light unexpected aspects that enlighten the researcher.

Developing a suitable research methodology is a process of self discovery. Compared with quantitative and scientific research methods, there are fewer guidelines on how to conduct action research in a scholarly manner. Understanding how to evaluate action research was one of the biggest hurdles that I faced. Coming from an engineering and science background, I was troubled that I could not justify decisions I made in a quantitative and objective manner. Developing my research around a set of case studies offered focus and framing (Section 4.1.1). Progressing through different case studies, I found the value in combining participant observation (Section 4.1.2) and reflective practice (Section 4.1.3), two methods that are complementary to an action research methodology (Figure 2).

4.1.1. Case Study Research Method

The case study research method (Yin 2013) allowed me to frame my investigations in real world contexts. Framing enabled clear discussion of the influence a specific setting played on the events that occurred during the case study. Under the broader hypothesis I was able to identify context specific questions to guide detailed analysis and evaluations. Outcomes from the case study analytical explorations may not have been generalisable
4. Methodology

Figure 2.: Methodology, a research journey
4. Methodology

beyond scenarios of the same framing conditions. By conducting multiple case studies within different settings, I was able to study across each case to make generalisations over the collective. Having explored three distinct case studies I was able to make more generalised claims.

4.1.2. Participant Observation

Another complementary research method I utilised was participant observation (Spradley 2016). Participant observation is very popular in the social sciences where the researcher becomes involved in the situation that s/he sets out to study. There are various degrees of participant observations, ranging from the more distant setup such as standing across a coffee shop to observe the shop patrons to being more involved by becoming a cafe regular and observing others while having a cuppa yourself. One can see straight away that a deeper level of participation opens up more intimate details to the researcher, but one also runs the risk of losing the big picture as well as invalidating the situations that one set out to observe in the first place.

The case study contexts were unfamiliar to me. I found it difficult to speculate on the operations of each of the case studies without participating in them myself and experiencing them first hand. Being in situ allowed me to quickly respond to unexpected scenarios and adapt my set up where required. Through in-depth participation I was able to identify opportunities for further analysis and critical moments for evaluation. Participating in the projects alongside my participants allowed me to build trust and rapport with them, which I believe contributed to the high participant retention rate for my case studies. I had people approaching to me requesting to take part in the study after the data collection had begun. They had seen me around and had seen the preliminary results from the case study. This would not have been possible had I not been present in the spaces and actively engaging the participants.

One shortcoming of in-depth participant observation was that it was difficult to maintain consistency with my field note-taking while fully engaged in the case study activities. Alas, this was the main motivation of the research: how to maintain an awareness of the overall situation without losing oneself in the process of working. Having been a participant myself, I observed everything from a restricted perspective and my observations were naturally subjective. This does not make the research less valid, as the claims I am making are still backed up with evidence.

Questionnaires, informal interviews and group focus discussions were also methods of investigation that I employed to evaluate the research. This brings us to the principle of action research: the real world is not a controlled test chamber so the subjectiveness
4. Methodology

should not be suppressed but be celebrated. Each case study itself is a process of hypothesis testing and evaluation.

The choice of participant observation was also a manifestation of the participatory nature of action research, specifically participatory action research (PAR). I actively engaged the host organisation and participants with proceedings of the case study. I took a knowledge sharing approach. I set up opportunities for discussions on the analytical and technical aspects of my research when interest was shown. I found once people became engaged in the topic they could offer more knowledge on the potential with the technology. I have found my time on-site and being present alongside my participants always provided me with chance discussions that were insightful.

Each of my participant observation studies were framed by the context that case study was situated in. It began by my initial exchanges with my host contact, often via a combination of email and video conferencing. Through these exchanges I gradually built a picture of the spatial context that I would set up. With two of the three case studies the equipment set up was planned and installed before I had the opportunity to observe the spaces in use. The tracking equipment installations were restricted by many physical factors (such as mounting locations and access), but I planned it to also correlate to the activities areas. For this I relied on the conversations with the hosts on how they perceived the spaces to be used.

For each case study, I adjust the planned layout when I arrived on-site. Following this, I installed and calibrated the indoor people monitoring system (IPMS). I then spent the duration of the on-site component of the case study working alongside my participants. I had a workspace similar to everyone else. I had a collaborative project with several people there. In my spare time I maintained and updated the tracking system and its analysis. Overall I tried to immerse myself within the context. I put on a friendly face and joined in on tea breaks, and exchanged pleasantries to others when I met them in the corridor. My experiences were not unlike a freshman turning up to work for the first time with unfamiliar faces and a new environment (both physical and social) to navigate. To my participants my presence was obvious initially, but by the conclusion of the on-site component I had become familiar enough to just walk in with no one batting an eye. This was to achieve complete participant observation and build rapport with my participants so I could gain an intrinsic understanding of their needs.

4.1.3. Reflective Practice

The strength of the case study method is in the interactivity with the context. Reflective practice (Schön 1992) guided the process of learning from the case studies. I acted both
4. Methodology

as the researcher and a future user of my research outcomes. I was able to switch hats at times, ask myself questions such as “Would this be too laborious for a manager to do on a daily basis?” and “How can I make this enjoyable and rewarding for my users?” Through reflective practice I was able to evaluate and refine my approach to case study design into the user-centric participant engagement strategy which is the focus of my findings.

Reflective practice was most effective when there is a space between self and the work. I practiced this in between case studies when I had the luxury to slowly digest the outcomes of the case study, critically examine the methods and choices I took, and let the reflections direct my preparation for the next case study.

My reflections were mainly conducted through writing. At the conclusion of each case I selected a collection of suitable scholarly publication outlets as a platform to present my work for peer review and feedback. I prepared my scholarly contributions to two fields of study. The technical aspects (system design, data processing and modelling) were submitted to engineering and computer science publications, and the applications of the system in the case study context were submitted to architecture and design publications.

My reflective thinking also influenced how I approached the next case study. I identified aspects of the case study that could be improved on. All of my case studies (except the last) were initiated by myself. My case studies were all situated in existing events. I sought opportunities that allowed me to expand on my previous case study, with more complex social context and technical requirement. Through this iterative process my system became more robust and increased in capability, and my user-centric people engagement strategy became more developed and achievable.

My three case studies represented the typical development process a business organisation may undertake to develop their own indoor tracking based management practice (Figure 3). My pilot case study echoes difficulties an organisation could have faced during their first forayed into indoor tracking: they may have a limited budget to build a prototype system and only recruited a small group of people as testers. After this initial attempt, I envisioned the organisation would be like myself, having gathered lessons learned to improve the robustness of the system, now ready to embark on the next step of capability and stress testing. In the second case study the hardware was required to handle a ten-fold increase in participants and an improved data structure. The increases in capacity brought new issues to light: how to manage the participant engagement in a way that maintained data quality. The much larger dataset and complex social structure allowed more in-depth data modelling and analysis. I reflected on my hectic experience trying to maintain full participant observation while keeping the system afloat. I was
4. Methodology

trying to maintain three roles at once: project manager, system maintenance personal and developer. I argue that my needs were not unlike a person in one of these roles. I used my experience to generate an analysis brief of processes. When I was approached to conduct indoor people tracking research with a professional design firm for my third case study, I realised this was the perfect scenario to test everything in the intended conditions for which they were designed. I was the organisation manager, confident in the system and now ready to deploy it to the rest of the organisation, like a captain that watched the boat being built in dry dock and come launch day ready to break the champagne as the boat sailed into water.

4.2. Case Study Design

The context of the case studies were selected to reflect three different scenarios of face-to-face collaborations in the real world. The first case study Discovery explored how a classroom was utilised by three groups of students during an intensive design studio class. The second case study Exploration looked at how an international design workshop operated in a large open space. Especially focused on how the behaviour of project groups evolved as the workshop progressed. The third case study Deployment tested the proposal that data from indoor tracking can provide insights on how a professional office operated.

With each case study, I was involved as an active participant in the activities, joining one of the observed teams’ project and contributing to its tasks. In the Discovery student design studio I was a project leader managing a group of students. In Exploration I was also one of the group leaders tasked with project management. In Deployment I was joined with two staff members from the host organisation on an internal research project.

The first two case studies were on self-contained events that I attended from the beginning to the end. The tracking data captured the concurrent group activities which operated under one workshop style schedule. The participants of the events had clear group allocations that allowed me to distinguish them into separate sets. I looked for patterns in the data that showed the development of face-to-face interactions as the group members became more familiar with each other and contributed to the group project to completion.

With the final case study, the nature of the observed activity was different, the activities did not begin and end with the tracking data collection. The tracking system was in place for many weeks, but in terms of the organisation’s operation it was only a snapshot of the daily activities in the office. Unlike with the workshop case studies,
4. Methodology

Figure 3.: The three case studies represented the typical development process a business organisation may undertake to develop their own indoor tracking based management practice.

Figure 4.: The tracking system developed to capture people movement and the analytics pipeline designed to study people behaviour.
4. Methodology

in the office environment it was not unusual for one staff member to be working on multiple projects at once, and depending on their roles, the time portion also varied. The projects themselves also varied in team composition, some were assigned to a single person and many others had different staff members contributing from week to week. In this case defining teams in terms of project assignments were not as black and white as with the first two case studies. Instead I selected to group people based on their department assignment. This allowed me to run analysis similar to Pentland’s organisational exploration-engagement analysis (Pentland 2014). I could then map the organisation’s interdepartmental face-to-face interactions with the project compositions.

Questionnaires were distributed to the case study participants at the conclusion of the tracking data phase. Feedback was collected on the participants’ experience during the data collection period, how they performed their tasks, whether they felt their behaviour has been altered due to the fact that they were observed, and their general opinions on team collaboration.

Host organisers and participants were consulted for analysis verification and insights. With the Deployment case study I was able to negotiate with the host organisation for access to their business operation data, which allowed me to conduct additional analysis.

Each case study consisted of the following stages (Figure 5):

1. Project preparation, including:
   a) Negotiation with host organisation on the terms of observation and data usage, apply and receive ethic approval from RMIT University
   b) Study the context and prepare preliminary data analytics scripts
   c) Equipment preparation based on preliminary site information

2. Fieldwork:
   a) System installation
   b) Participant recruitment and briefing
   c) Begin data collection (tracking data, participant observation, supplementary datasets)
   d) Evaluate data quality and apply adaptation as required
   e) Negotiate additional contextual data such as participant attributes
   f) Conduct participant engagements (focus group meetings, presentations, interviews)
   g) Improve data analytics
4. Methodology

3. Post field work analysis and evaluation
   a) Distribute and analyse questionnaires
   b) Overall tracking data analysis and cross evaluation with observation notes and questionnaire responses

4.2.1. Preparation Stage

The case study preparation stage lays the foundation of the case study. Although it is impossible to foresee all complications and plan the appropriate responses, I have found that thorough preparation in terms of data collection tools and the establishment of good communication with the host organisation were critical for getting me to “hit the ground running” with the data collection.

The ZigBee-based IPMS was designed to be self-contained and scalable. This set up has many benefit. I was able to fully test the system before deployment. Once I arrived on-site I could quickly deploy it and began data capturing straightway. With stream data analytics in place, I could review the data quality in real time and make adjustments to layout if needed. The IPMS and its deployment process was refined over the three case studies to be more robust, automated and user-friendly. I adapted many of the post data capturing analytics from the previous case studies into real time data analytic for the next. By the third case study, my set up was so portable that I was able to transport the complete hardware set up in standard suitcase through checked-in luggage. I was able to unpack and have the whole system installed and started data capturing within few hours of having arrived on-site.

As per university regulations, ethical approval was required for the commencement of all my case study data collections. I utilised the ethics application process as a methods of participant engagement with the host organisations. This is complimentary to engagement contract. Through my contacts with the organisation I maintained ongoing transparency with my process. I have received feedback from the organisations that they appreciated the formality that I went through to establish the engagement parameters. For example with the Exploration case study the university who hosted the workshop was explicit in their request for information for the protection of their staff privacy. I generated floor plans indicating the locations and field of views of the time-lapse cameras showing no staff areas would be captured, and explained that with the nature of camera set up, people walking through the camera view will be blurred and facial features unidentifiable. The university was satisfied with this explanation, and in addition
4. Methodology

Figure 5.: My example case study timeline, showing my interactions with my case study stakeholders
4. Methodology

offered support from the IT department to assist me in finalising the locations of sensor mounts prior my arrival on-site.

4.2.2. Fieldwork

Another important factor for the success of the data collection is being flexible to possible changes in plans or discrepancy in expectations but be clear with the limitations and guidelines.

I have had many encounters with system installation difficulties; it could be limited mounting options, limited reach to power and other cabling or unforeseen interference in reception. The tracking sensor beacon locations were not hard coded but stored in a file for analysis script to read. Tracking sensor accuracy was tested after the installations were finalised. I also had back up devices to replace faulty components, as well as conduct separate collection when I identify opportunities to do so.

Once ethics approval was granted there were possibilities for minor amendments. The amendment process has a shorter turnaround with my university. This allowed me to build in flexibility to expand my data collection when I observe opportunities while on-site. I have used the amendment process to adjust the planned questionnaire questions, conduct additional interviews and incorporate other contextual datasets that I received from the host organisation into my analysis.

Data analysis was a mixture of quantitative and qualitative approaches. Based on the tracking data I have developed a **Dynamic Social Interaction Network Model (DSINM)** (Williams, Burry, and Rao 2015a, A.5) that can be adapted to different social contexts and environments. The DSINM was applied to the live data as they were streaming in. Live data reporting was configured for the dual purpose of system maintenance and participant engagement. System performance reported on the participant numbers and sensor status. These were to be acted on by myself or another person in charge of system maintenance. With an automated data collection system it is all-important to have built-in methods for system checks and data verifications. There is nothing more disappointing than having completed data collection only to discover the data captured is useless.

Live data analysis and visualisations were designed to engage the participants in the data collection process: providing them useful and interesting insights, enticing them to continue participating (by carry their tracking sensors) and get feedback on developing context relevant analysis visualisations.

The set of investigations that applied to the tracking data came from multiple sources: relevant methods from literature, my personal participant observation, and those nomi-
4. Methodology

Through my participation in the case study activities I was able to develop a sense of what information I would like to have at hand during the case study activities. Those ranged from “Where my team like to work and how I could support that?” to “What other people are up to, I wonder whether they are not too busy for a chat right now?” As I was physically present in the space with my participants I also gathered many requests from them; participants whom I was viewing as my hypothetical clients. People were interested to see where they have been and how their team operated in comparison to others. The difference between recollection, expectation and data always prompted discussions of self-reflection and constructive feedback for data analysis. I explored graphical ways beyond basic network and statics visualisations to demonstrate the dynamics of team-based interactions; this completed a system that is capable of providing real time insight to the organisation.

4.2.3. Analysis

The goal of my research was to provide people with the insights from the tracking data so that they are convinced to take on this exercise themselves. To move from raw data to insight is where professional assistance would be useful. A major part of my research was to explore analytical methods from other scientific fields that can be operated on the tracking data. Fields I focused on were data mining, statistical analysis, social network analysis, information visualisation and visual analytics. The field of options are so large and varied that one would easily lose sight of the objectives while perusing all possible options. I made one distinction while I searched: I would only use analytical methods that are simplistic in theory and adaptation. I wished to be able to communicate the theoretical underpinnings of the methods of I incorporate into my analysis toolset to my participants, who may or may not have the background or appetite for complex mathematics. Although it is tempting to say, “I used machine learning/artificial intelligence/Big Data theory to get those results”, inferring “it’s a magic wand and trust me it works”, it does not help my participants and the organisation to comprehend what was being done to their data. It put a barrier in discussion, which can deter people from inputting. I strived to use methods that can be explained in simple terms and diagrams. I believe this helps to dispense people’s fear of data misinterpretation and misuse.
4. Methodology

The Data Processing Pipeline

The tracking data analysis followed a pipeline-like process: cleaning, modelling, analysis and presentation (Figure 4). The cleaning stage took the raw data from the database and removed incorrect data caused by environmental interference and instrument inaccuracy. It also conducted low level data redundancy through data sampling. The data modelling stage was to construct a behavioural model from the cleaned data to represent the behaviours of interest. Statistical, social and complex network analysis methods were applied to the behaviour model to give insights on the important actors and interactions captured by the data. Those insights were presented graphically for easy and quick interpretation.

Behaviour Modelling

I have designed two processing pipelines using different behaviour modelling approaches: a signal processing based approach and a complex network based approach (Figure 6). The intuition of the signal processing based approach was to process the tag data independently before performing association analysis in order to convert it into tag-tag interactions.
4. Methodology

pairwise links for further network analysis. A network is a graph structure consisting of a set of nodes and a list of links that connect them. A network is known as bipartite when there is a distinction made that separates its nodes into two sets and only allows links connecting nodes from different sets. The motivation behind the complex network approach is to consider the tracking system as a bipartite network where the two node sets are the tracking beacons and the tags, links between the two node sets are the data entries. Idle tag detection and the data reduction process are handled through network manipulation. This work is reported in “Graph mining indoor tracking data for social interaction analysis” (2015a, see Appendix A.5).

My work has shown that an adaptable process with adjustable parameters allowed it to be customised to complex environments and behaviours in the real world. It is also beneficial to set up multiple concurrent modelling pipelines that represent different behaviours of interest, for example, one to focus on close collaborative interactions and another to monitor brief social exchanges.

Analysis for Insight

In a less than ideal world, direct application of existing methods is often problematic. One might have data in incompatible format that requires pre-processing, for example simplifying a weighted network to an un-weighted one. Then it may bring back unexpected results, which take further unravelling to determine the source of the discrepancy, whether it was due noisy data or incorrect data model. Once those issues are resolved satisfactorily, one will then face the hard task of interpreting the analysis outputs.

I found many intermediate results helped form a more comprehensive representation of the situation. Sequences of visualisations depicting data moving through the analysis pipeline builds a storyline to communicate results from complex theories. Many of the earlier analysis results also shine light on fascinating aspect of the data that became buried by subsequent processing.

I used this exploratory approach when I examined the data from my case studies. It is similar to wood carving, where a craftsman must first understand the material he is working with before he can set to bring to life the spirit within. With a change in perspective I speculated that those intermediate results would also help my clients to understand the situation that the data recorded as well as the theory behind the analysis. The viewers learn how to read the visuals presented from the more comprehensive understanding of what and how means. This allows these visuals to be used in ongoing iterative feedback setup that can be integrated into an organisation’s daily practice.

SNA is a well-established field of research that I have referred to for analytical methods.
4. Methodology

Data generated with my case studies are unlike common dataset used in SNA research: my data is dense and noisy compared with well known small datasets used for evaluation purposes and they are not large enough to be considered as Big Data. With this premise I worked on translating and interpreting SNA theories for my data modelling, and equally important, communicate and convince the use of these theories to people unfamiliar with them.

Result Presentation

I have taken the exploratory approach by freely combining methods and theories with my own interpretations to bring to light interesting phenomena.

There were two versions of the data presentation used in this research: an online version and an offline version. The online visualisation was used during the data collection phase of the case study. Its purpose was to provide simple analysis to engage participants and provide real time updates to monitor the tracking system. The analyses were focused on delivery of a range of snapshot insights. The offline visualisation was used in the post collection phase, in which longitude analyses were conducted.

Online Visualisation The aim of online visualisations was to offer the participants a quick overview of the current situation. With their unique tag identification (ID) they could look up their own data, to confirm that the data has been correctly captured and learn from analyses on their behaviour. Individual data was also presented alongside others so comparisons could be drawn. Analysis was also conducted on a subset of the data, grouped by certain tag associations such as project group assignment. This allows individuals to be kept up-to-date with the movement of their group, and provide insights on group dynamics to the project leader.

The approach I took with the online visualisation was not to make them cognitively complex, but to have them light on information, with less data points per graph and light on graphics intensity. I did not try to design the one graph or layout for everyone, but aimed to have a selection so that people could pick the few that they found useful to follow. In the case studies, I had a simple one page website set up that grouped the visualisations into themes. In the future one could design a better layout, or even multiple pages that target different needs, or a dashboard set up that an individual can customise.

Longitudinal Analysis After the conclusion of the data collection stage, I had time to explore more complex analysis and visualisation strategies. The focus of the exploration
4. Methodology

shifted from real time processing to longitudinal analysis. With the complete dataset at hand I looked for trends, patterns and pivot points that indicated changes in people’s behaviour. I cross-referenced those with observation notes and photographs to decipher possible underlining causes in the behaviour changes.

This was an iterative process as I moved between the quantitative tracking data and qualitative contextual evidence. With each iteration I refined my analysis methods and fine-tuned simulation parameters. I was able to shift through the time dimension, adjusting time windows and analysis parameters, which enabled the process to uncover the most representative data points for a behaviour of interest. This process was akin to photography where the parameters were camera settings that I played with to bring out one aspect of the view into sharp focus. This set of parameters formed my hypothesis, which I then extended to the whole dataset to test. At this point data visualisation became a necessity to allow me to scan through a large amount of results. I used a variety of visual analytical techniques from static 2-dimensional graphs to more complex animated and interactive visualisations. This highlighted other occurrences from across the temporal and spatial dimensions as well as different group attributes for which similar behaviours might have occurred. I then verified my hypothesis by referring to my time-lapse photographs and observation notes. This informed my options for the next iteration: I would refine the parameters, or the analysis process, or explore another possible behaviour that these brought to my attention.

This was also an explorative process. With the quantity and range of interesting leads uncovered with each iteration it was impossible to explore them all systematically. The aim of this stage of research was not to prove generalised behaviour causation or trends, but to explore methods and strategies to bring those possible occurrences to light. It was intended to provide feedback discussion points in the decision-making and review. The target users were people within the organisations with contextual knowledge (see Spotlight on a user-centric approach). As I practiced participant observation during my case studies, it was easy to put myself in their shoes and envision what insights could be used for my intended users, and equally important, how to present these insights to them. When I was presented with multiple leads to explore during data analysis, I would refer to my target users when making decisions on what path to take.

This user-centric approach was also effective to communicate the data findings and explain the methods used to an interested audience in an accessible non-technical way. I did not use a one-size-fits-all graphics, but instead designed sets of visualisations to present aspects of the findings to different audiences.
4. Methodology

<table>
<thead>
<tr>
<th>Spotlight on the user-centric approach: my targeted users</th>
</tr>
</thead>
<tbody>
<tr>
<td>I have selected three user groups to represent stakeholders in the case studies. This approach helped focus the analysis and discussion of my research. I compiled them from the people I met and observed during the participant observations.</td>
</tr>
<tr>
<td>These user groups were: participating individuals who wore the tracking tag; project leaders and the office manager or activity coordinator.</td>
</tr>
<tr>
<td>Participants signed up to the study because they were curious about the tracking technology and what their data would reveal compared to their co-workers.</td>
</tr>
<tr>
<td>A project leader wished for insight that could help him better manage and plan his projects. He had been considering changing meeting times and was keen to use this opportunity to test a few schedules.</td>
</tr>
<tr>
<td>The office manager was eager to receive some quantitative data on how the office spaces were used by the occupants. She planned the layout with consideration to different needs, and now they were occupied it was time for a review. She wanted the system to identify potential underutilisation. She was also interested to see how the staff socialised within the space, and open to feedback on the social cohesion within the office.</td>
</tr>
</tbody>
</table>

4.3. Methods of Evaluation

I have divided the research into two components for evaluation. The first is the hardware: the indoor tracking and data analytics systems. The task for this component was to capture people’s location information as they go about their normal activities within the observed space, and represent their behaviours as accurate as possible in a numerical model. This component of the research was quantitative in nature; it more closely resembled solving an engineering design problem. This research has been published in peer-reviewed engineering and computer science conferences (Williams et al. 2015b; Williams, Burry, and Rao 2015a, A.4, A.5).

The second is the strategy to integrate this system into professional practice. This is the deployment component: it is a qualitative sociological study divided into three distinct case studies. The evaluation of this component is based on the successful conduct of the case study, interaction with the participants in an ethical way, the responses of the participants to the tasks given, and the report of issues raised and their resolution. The first two of the three case studies have been published in peer-reviewed Architecture and Design conferences (Williams, Burry, and Rao 2014b; Williams, Burry, and Rao 2015b, A.3, A.6).
4. Methodology

4.3.1. Hardware

Rigorous systematic testing was applied to evaluate the performance of the indoor tracking and analytics systems. The performance of an indoor tracking system is sensitive to the layout of interfering objects in the signal path. During each of the case studies an on-site position accuracy test was conducted. On average the accuracy was found to be approximately 2 meters, with variations between the three case studies. The current state of the art indoor tracking system has sub-meter accuracy performance (Microsoft 2016), but those sophisticated systems were suited to the budget and portability requirement I needed for my case studies. I worked with the fact that it was not possible to pinpoint tag wearing persons to a seat at a given time, but the precision I had was sufficient, when accumulated over time, to build a picture of the person’s behaviour with other people and the space they shared.

My people analysis scripts construct a narrative of the interactions between people and their environment. The first test of its performance should always be whether it “makes sense”. The best judge of that are the people who were represented by the data. It is a big tick if a participant sees an overview of the results and says, “I remember experiencing this”. Only when this test is passed we can safely move on to identify events that were surprising and discuss possible reasons and responses.

Analysis scripts were constructed in a pipeline structure, taking the raw data through different stages of data processing and modelling. I have taken the narrative approach in presenting insights. Data from the intermediate stages that are traditionally hidden from people other than system administrator were brought to attention. Instead of presenting a composed infogram, I designed the data report to take the viewer through the data analysis process. With the data explained this way the viewer receives a more comprehensive understanding of what is presented. This way the viewer has more trust in the result because they can understand the process that got it there. Developing the analysis script was the focus of the Exploration case study (with the findings published in Williams et al. 2015a; Williams, Burry, and Rao 2015a, see Appendices A.4 and A.5) and Deployment explored the narrative reporting further.

A knowledge sharing approach is essential to my PAR methodology. To successfully integrate a new system into existing organisational practice, it is critical to provide the organisation with not only the system, but also the knowledge of how to operate it. Moreover, showing people the process so that they can replicate and adopt it is far more useful than the final outcome. The Deployment case study is a successful example of this.
4. Methodology

4.3.2. Deployment

A successful system integration strategy needs to satisfy the following: conduct the case study in an ethical manner, carry out planned data collection tasks, maintain rapport with the participants, cultivate participant contribution, confirm the analysis results from the participants.

As my research was taken within the RMIT University, my interactions with my participants complied with the university’s human ethics code as reviewed by the university’s human ethics board. The process of seeking approval within an institution may be more stringent than what a business organisation may require when conduct internal studies, but it does not mean that business organisations should be any less ethical in planning and delivering their exercises. I disagree with the view that the ethical approval process is restrictive and ill-suited to a case study methodology. As I will demonstrate with my case studies, it is beneficial to embrace the ethics application process as a method of initiating participant engagement. Through negotiating the terms of engagement with the host organisation I demonstrate my respect of their culture and their people. With my institution, there were more possibilities for minor amendments once ethics approval was granted. This allowed me to build in flexibility to expand my data collection when I observed opportunities while on-site. I have used the amendment process to adjust the planned questionnaire questions, conduct additional interviews and incorporate other contextual datasets that I received from the host organisation into my analysis.

Data collection is a major component of case study research, without data there is no evidence to back up any findings. Data collection is also very difficult within the case study methodology, as researchers are heading into specific cases collecting very detailed but highly contextual data. Through my work I have realised the importance of in collecting multiple forms of data to cross-reference against each other and supply additional contexts. For example, I collect people location data using my tracking devices as my main data source, but I also use fixed camera to take time-lapse photographs to confirm social activities. With the complete participant observation technique I was not able to take consistent written field notes, but I took a log of eventful activities that I felt were worth modelling with the tracking data. The time-lapse photographs provided evidence to back up the tracking data behaviour model.

Building and maintaining ongoing rapport with the participants is critical for collecting good quality data that is representative of the situation that we wish to capture. Some people may have reservations regarding interaction with their subjects for fear of influencing the data. I argue that while this may be the case with experiments using well established data collection methods and equipment, but when participants are faced
4. Methodology

with unfamiliar technology and systems, even the most “tech savvy” people will require initiation to fully understand what is required of them. For the people that were less interested in the technology, they responded well when presented with the social benefit.

In the last case study, I explored strategies to maintain positive engagements with my participants as a response to multiple issues I identified in my earlier case studies. I have found that data quality dropped with time as more and more people were forgetting to carry their tags as per instructed. I built data processing scripts that identified individuals that were forgetful; I then recruited office support staff to undertake the task of checking and reminding people to wear their tags. This way I harnessed the existing social cohesion without negatively impacting my relationship with the participants.

While I was on-site I explored ways to drew people’s attention to the tracking data in an informative and fun way. I engaged participants in casual conversation to collect suggestions on what would be useful for them. I interpreted those suggestions into behaviour models and live data visualisations. Another effective source of inspiration came from unscheduled one-off social events. I was more experimental and playful with these visualisations, and I had great responses from the participants. (see Spotlight on capturing the moment in Chapter 8).

The suggestions contributed by participants were the major component of the data analysis brief. As the purpose of the analysis was to report insights to the stakeholders, one task of my participant observation was to collect suggestions from the participants. I actively cultivated participant interest in the tracking activity project, providing many opportunities for participants to voice their ideas. Question and answer sessions during with each presentation, focus group meetings and informal chats during breaks provided a varied platform from which I cast a wide net to capture ideas. My constant presence and cultivated approachability make it easy for people to communicate their thoughts. I aimed to have a quick response to their suggestions, which in turn rewarded their contribution and they returned with double-fold enthusiasm.

Online questionnaires were distributed to all the participants at the conclusion of the data collection period, but I found the response rate was low (around 10%). On the positive side the ones that took the effort to reply provided very detailed responses. I found that a more effective way was to utilise my interactions with my participants to gather feedback on the analysis results. At formal meetings I always provided a condensed update on the visualisation and interesting findings. When I saw people informally I asked whether they had seen the visualisations recently and used that as a lead in to ask for feedback and suggestions. I found these times people where more forthcoming with their thoughts.
4. Methodology

4.4. What’s Next

In the next few chapters I will be diving deeper into case studies, using each to highlight one component of the participant driven people tracking: the first case study *Discovery* (Chapter 6) will discuss on how to select the hardware, second case study *Exploration* (Chapter 7) focus on methods of analysis and visualisations and third case study *Deployment* (Chapter 8) wraps up with strategies to integrate people tracking into everyday business practices.
5. Introducing the Case Studies

With the experiences I have in collaborative projects, mainly in university design courses or industrial workshop settings, I felt more satisfied with the outcome of the collaboration when there were active discussions and idea contributions from all members of the team. I also recall moments when we could not come to a consensus as a team or productivity was interrupted by meetings, so I was interested to explore how a balance could be found between group interactions and individual work. In reading research into physical interactions in workplaces and as well as the field of collective creativity, I found the literature undecided on the quantity and quality of interaction that is optimal (Boutellier et al. 2008; Haynes 2008). With teaching design studios and other workshop-like events available to me as part of the SIAL research group, I have had access to data opportunities to contribute to this area of research.

The case study methodology allows me to delve deeper into specific cases to explore issues and solutions that arise from close engagement with my subjects. It is important to note certain issues are specific to a case. In a different context that issue may play a less dominant role. Participant observation combined with reflective practice on my part as the observer allowed me to explore issues fully within their context. This is the importance of participant observation, observing people operating within the real world environment; it brought me closer to the stakeholders and their motivations. I was careful to distinguish influence that I personally exerted on the scenario as an observer, researcher, outsider and participator. After conducting three case studies in different contexts I can ascertain with confidence as to which aspects are context specific, which strategies that I engaged were transferable, and what generalised lessons could be learned.

This series of three case studies were selected to resemble different stages within the process a real world organisation would undertake to initialise the practice of people tracking for management insights. The first case study Discovery (Chapter 6) represented the pilot study one would take to design the equipment and system for collecting data. The second case study (Chapter 7) is the Exploration stage where a full scale testing was done for a short duration and data collected was used to develop the data
5. Introducing the Case Studies

processing and analysis pipeline. The third case study Deployment (Chapter 8) simulated the deployment of the tracking system into an organisation’s ongoing daily practice.
6. Case Study 1: Discovery

The *Discovery* case study was my initial approach to tackle a study of people interactions in the real world. This brought to light issues that many people and organisations would face while initiating a similar set up at their practice. As with any pilot study, I was limited by budget and precedents to follow. The brief was open: an operational prototype that can record people movement data.

I present my arguments on technology selection and deployment set up. I will also discuss strategies to mediate participant engagement when there is a power relationship in place.

Sections of this chapter has been previously published in “Understanding social behaviors in the indoor environment: A complex network approach” (Williams, Burry, and Rao 2014b, see Appendix A.3).

6.1. Motivation

I had explored collaborative interactions in two previous case studies by analysing people’s interactions with their tools (Williams et al. 2013, A.1) and meeting discussion threads (Williams, Burry, and Rao 2014a, A.2). I had experimented with SNA methods using another dataset of project notes, and had success in using SNA centrality methods to uncover points in the dataset that corresponded to pivotal movements in the project. I wished to carry out similar analysis with new projects, but noting the laborious process of coding the project note data, I desired for a system that could automate the data capturing process. I was open to the idea of capturing a different data type that also represented the dynamics of a project in progress.

6.2. Equipment Selection

*Discovery* was the first of my case studies to incorporate an automated wearable sensor data collection system.

I had experiences with participant observation in my earlier case studies which were
6. Case Study 1: Discovery

Figure 7.: The workspace (top) and layout (bottom).
6. Case Study 1: Discovery

<table>
<thead>
<tr>
<th>The Context of the Discovery Case Study</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Activity:</strong> A university intensive mode design workshop</td>
</tr>
<tr>
<td><strong>Duration:</strong> Six days</td>
</tr>
<tr>
<td><strong>People:</strong> Studio teaching staff and students. The students were divided into three project groups; a tutor prepared the design tasks and led each group.</td>
</tr>
<tr>
<td><strong>Space:</strong> The three groups shared one classroom for the duration of the studio; sections of the room were allocated to different groups.</td>
</tr>
<tr>
<td><strong>Data collected:</strong> Six days of people tracking data (fourteen people) and time-lapse photos in the workshop space.</td>
</tr>
<tr>
<td><strong>Data collection method:</strong> Complete participant observation and automated data collection. I was one of the three tutors in the workshop.</td>
</tr>
</tbody>
</table>

set back by the difficulty of collecting consistent field note data. Researchers in design processes (Kan, Bilda, and Gero 2007; Gero 2010) and productivity management (Boutellier et al. 2008) echoed my frustration. Data collection methods used by productivity research are mainly from employee questionnaires and observation notes. The research on collective creativity is mostly based on data collection from a strict experimental setup. In these fields, academic studies were confined to small-scale laboratory style settings where the laborious data transcribing process was more manageable. I found the established methodologies hard to be adapted within a live design workshop setting. This lack of effective data collection methods can hinder the adaptation of academic research into real work practices.

The field of pervasive and ubiquitous computing offers exciting technical solutions in the live capture of people’s activities. Although the focus of pervasive and ubiquitous computing research has been on proof of concept and advances in technical accuracies, I could see the potential of coupling those systems with advanced data modelling to provide real time people interaction insights that represented the interactions that I sought.

Purpose built systems demonstrated the possibilities. The Human Dynamics Laboratory group at Massachusetts Institute of Technology has developed a multi-sensor badge for people interaction applications that has been trialled in several large corporate organisations (Waber 2013). I was attracted by their system’s success in improving office productivity (Waber et al. 2010), but wished for a system that used commercially available components and a flexible data processing structure.

Recently, developments in wireless and wearable sensors have brought high-precision tracking systems to the consumer level. Many ready-to-use devices paired with accessible
software development platforms are available at the click of a button. They are marketed for commercial applications such as context-aware marketing and inventory management. I saw an opportunity to configure these devices to collect data on people’s movements.

After surveying various systems, I selected an off-the-shelf ZigBee tracking system. It is a wireless sensor network system that utilises the ZigBee communication protocol. The set up consists of a set of beacons and wearable tags. As the tags move through the reception zones of the beacons, the system automatically tracks the location of the tags in relation to the beacons. It has several advantages. Compared to a camera-based people recognition system that requires complex algorithms to detect and match individuals’ features, a wearable wireless sensor network (WSN) system detection process is simpler and does not store identifiable information of the individual. The ZigBee system I selected was originally designed for inventory tracking applications. It comes in a self-contained package that requires minimal system level configuration to begin outputting data. It is also scalable, more tags or beacons can be bought at a later date, and can be easily configured to operate within the existing set up. I configured a Raspberry Pi, a single board computer, to host a database to capture the data that streamed out of the ZigBee tracking system. For more information, see Spotlight on wireless sensor network (WSN) based people tracking.

For this case study, the IPMS (version 1.0) comprised a ZigBee-based indoor tracking system and a webcam-based time-lapse photography system (Figure 8). The IPMS was installed in the space where the three workshop projects operated. I recruited fourteen workshop participants (four tutors and ten students) to participate in the people tracking data collection by wearing a tracking tag during the workshop period.

6.3. Evaluation

This case study was evaluated on three aspects: people, technology and analysis.

6.3.1. People

Managing successful participant engagement is fundamental for any human-based study; if all of our participants quit, we would end up having no data to study. University guidelines were followed to ensure the study was conducted in an ethical manner. I ensured that my teaching relationship with the students had minimal interference to their consent to voluntary participation in my study by making the voluntary nature of participation and the ability to withdraw at any time clear in the written statement to potential participants.
6. Case Study 1: Discovery

Figure 8.: The first version of the indoor people monitoring system (IPMS).

Figure 8.: The first version of the indoor people monitoring system (IPMS).
6. Case Study 1: Discovery

<table>
<thead>
<tr>
<th>Spotlight on wireless sensor network (WSN) based people tracking</th>
</tr>
</thead>
<tbody>
<tr>
<td>There are two general approaches to people tracking: a locationing approach where you are interested in where people have been, and a positioning approach where the precise coordinates of the person are needed.</td>
</tr>
<tr>
<td>The locationing approach is suited to scenarios when the program of the space is known and where beacons are placed at locations of interest to study how people interacted with them throughout the day. For example, one can obtain a vivid picture of the social atmosphere of the office by placing beacons in people’s workstations, meeting rooms and social spaces such as the coffee machine and lunch tables.</td>
</tr>
<tr>
<td>The positioning approach is more suited to an open plan space with a flexible program, such as large function rooms or theatres. A gridded beacon layout minimises signal bias.</td>
</tr>
<tr>
<td>Both approaches can be set up using a typical WSN which comprised of two set of devices: a set of mobile devices called tags that are worn by the person that identifies them in this sensor network, and a set of stationary devices called beacons that act as reference nodes in the network. The underlying assumption is that the signal strength between the beacons and tags (known as the received signal strength indicator (RSSI)) are inversely-proportional to their distances. In the case of the locationing approach, a tag is assumed to be at the location of the strongest detected beacon if their RSSI is within a threshold. With the positioning approach several beacon RSSIs are used to calculate the coordinate of the tag by trilateration or other methods.</td>
</tr>
<tr>
<td>The ZigBee system I used has two output modes. The base mode output a tag-beacon data structure of [tagID, beaconID, RSSI] for all detected tags and their strongest-detected beacons within the network at six-second intervals. The extended mode outputs three beacon data per tag with the data structure of [tagID, beaconID1, RSSI1, beaconID2, RSSI2, beaconID3, RSSI3] at three-second intervals.</td>
</tr>
<tr>
<td>I used the base mode ZigBee system for Discovery. The extended mode was used in the next two Exploration and Deployment case studies.</td>
</tr>
<tr>
<td>It is to be noted that although the base mode lends itself to the locationing tracking approach, and extended mode to positioning, a change in approach is possible. When using the extended mode for locationing, one merely drops the extra beacon data (see Williams, Burry, and Rao 2015a, A.5, for more details). I have developed a placement algorithm that simulated people’s movement, thus estimating people’s...</td>
</tr>
</tbody>
</table>
6. Case Study 1: Discovery

positions with only locationing approach data (see Williams, Burry, and Rao 2014b, and Appendix B.1).
6. Case Study 1: Discovery

Attract Participants

I was one of the three teaching staff that led projects in this workshop-style design studio. The students that enrolled in the studio had free choice of the three offered projects. My project was intrinsically linked to the tracking study: my students were expected to explore applications based on the people tracking technology. At the very first studio session, I presented my research to all of the students and explained the nature of my case study with the project offered: as part of my research on collaborative interactions I wished to observe all the staff and students involved in the studio. Time-lapse cameras were used to take photos at regular intervals, tracking equipment were installed and tags distributed to people that signed up to the tracking component of the experiment. I encouraged everyone to sign up to the tracking experiment, explicitly stating that their participation in the tracking would not interfere with their participation in their selected project activities: they do not have to be tracked to do my project and they do not need to be in my project to participate in the tracking. Being part of my project, my students would have access to the anonymised data. I made it clear to the students that this was a pilot study, so I could not guarantee the quality of the data if they chose to use it, but I welcomed input from them to work on improving the system together.

I was successful in engaging all of the twenty students and staff to participate in my case study. Twelve students and four staff (including myself) were tracked with a ZigBee tag for the duration of the studio. Four students chose to participate in my project. They conducted space surveying, system maintenance and testing as part of their work. These activities produced information which were mutually beneficial to everyone involved in the project.

My participant observation was successful in two aspects. My role as a project leader exposed me to what information would be useful for a project manager. Working alongside other people gave me the opportunity to observe the different behaviours and interactions that occurred in this shared workspace. This formed the brief for my data analysis, where I explored ways to model these behaviours with the tracking data that I collected.

Participant Input

Not everything was smooth sailing, but challenges present opportunities. My relative inexperience with participant observation as a form of data collection became apparent very early on. I was trying to maintain too many roles at once: coordinating my project with my students while at the same time trying to keep the tracking system afloat
6. Case Study 1: Discovery

and keeping field notes. When the students showed interest in the technical aspects of
the system, I allocated several system maintenance tasks to them. They were happy
with the extra work in exchange for the higher level of access to the data, were more
diligent in carrying the tags with them and were more engaged with the tracking project
compared with the rest of the participants (Figure 9). They benefited from the technical
interactions with the system and accomplished their project of building an Android
application to visualise the live tracking data (Salim et al. 2014). This gave me the idea
that an increase in the user involvement with the technical operations produces better
data, because the participants gained a sense of ownership with the people tracking
process and would be more diligent in the following the instructions. I explored this
further in the third case study conducted in a professional office, where I recruited the
office’s staff to help in system maintenance and participant management. They were
successful in their tasks and were able to maintain the data quality in my absence.

6.3.2. Technology

The intention of the tracking system was to capture how people operated within a
shared workspace environment. I was interested in how space planning shaped social
interactions between the occupants. Specifically, I wanted to see where the interactions
occurred between people not working on the same project.

Three project groups shared the classroom-like workspace (Figure 10). The project
leaders met to decide on the space allocation before the students arrived. One project
leader requested the back of the room where he cleared a section of the floor space
to store materials and conduct large size construction with his group (blue). Another
project leader was also interested in the more open space towards the back; he set up a
long table to conduct water-based experiments that might get messy (red). My group
had the front corner of the room where I laid out my electronics (green).

The locations of the beacons were restricted by the access to power and mounting
points. I placed nine beacons on tables where they were plugged into the power boards
that the occupants shared.

In this case study, the basic mode ZigBee system was used. I was concerned that
the RaspberryPi single board computer hosting the Structured Query Language (SQL)
database may not be powerful and stable enough to capture the ZigBee data for the
whole duration. A python script regularly queried the database to generate a status
report that I used to monitor the database. I had regular database back ups, this
ensured that despite several system interruptions, I was able to recover the majority of
the data generated during the full duration of the study.
Figure 9.: The mobility of the projects. The solid shading indicated time spent at the group’s assigned desks, and the unshaded times were spent in the classroom but not within their assigned space. The Project 1 (green) was led by me (P1), and the P1b1 and P1b2 were the students who assisted me with the system maintenance. Although most of the students had full attendance during the workshop, as you can see from the diagram my group’s data was more consistent compared to other participants. The other participants did not formally withdraw from the project, rather they all forgot about bringing the tracking tags back to class with them when their work got busy. This demonstrated that close engagement with the tracking process positively contributed to participation rate.
6. Case Study 1: Discovery

Figure 10: *Discovery* workshop space with project assigned spaces highlighted with different colours. Green was assigned to my group P1, as a group we explored people tracking applications. Red was assigned to P2, the project work was all individual based. Blue was assigned to P3, the project included initial group work and then broke up into individual work.
6. Case Study 1: Discovery

I had a good representation of the occupants in the tracking data. Fourteen tags were distributed to one studio coordinator, three project leaders (including me) and ten students. My project contributed four tagged students and three from other two projects. The tags were scanned at approximately six second intervals, resulting in 125,063 tag-location data pairs over the six days of recording.

There were limitations to the tracking system that I needed to work with. Through testing (Figure 11), the ZigBee system was found to provide an average tracking performance of True Positives (TP)=79% when recording transition between two beacons placed ten metres apart, using two tags (Figure 11, line plot). The corresponding signal strength reading was also recorded (Figure 11, circles). As seen in the testing results, the signal strength outputs are an unreliable representation of the precise distance, as they were sensitive to the placement of obstacles (such as people and furniture). In a complex everyday environment, the performance deteriorates greatly. This is because the ZigBee WSN operates within the 2.4GHz frequency, (stationary and mobile). Obstacles and surfaces distorted signal paths of the wireless modules, and everyday material such as water, metal and concrete contributed to this interference. The human body (which is mostly water) is very effective in blocking the signal. This made tracking tags worn on the person unpredictable, as depending on where the tag is carried the body mass blocks signals from that direction. The ideal location for tag attachment would be on people’s heads, but the more practical alternative is on the table where they work and to take with them when they move. In this case study tags were provided with a clip that people could use to attach the tags to their clothing, but I observed most people left theirs on their desk during the day and few carried theirs in their pockets or their bag, none of which was ideal. As I mentioned before, the people who most diligently followed the instructions were my students who were working closely with the system. It was to their benefit that the best data was captured. For others, there was less to gain.

I negotiated the technical limitations by focusing on the initial brief. I was interested in how the space arrangement enabled people interactions. The beacon locations corresponded to the spaces of interest, which can be extracted by looking at the tag-beacon registration without the unreliable RSSI data. The false positives were mainly high frequency fluctuation, which I removed using a moving filter (Figure 12). These measures were effective in extracting data that I could analyse for behaviour study.
6. Case Study 1: Discovery

Figure 11.: ZigBee tracking system performance testing using two beacons placed ten metres apart and two tags moving along the direct connecting path. The solid line represents the registered beacon (Receiver 1 or 2), the circles are the detected signal strength. On its own, the signal strength measure is not reliable enough to be used to represent distance. On the other hand, the beacon registration performance could be improved with post data processing as seen in Figure 12.

Figure 12.: Data smoothing applied to raw beacon registration data collected from the case study. The 1 minute moving filter was able to remove the short peak false registrations without compromising the tracking of the general movement of people between their work stations.
6.3.3. Analysis

The aim of the case study was to reveal the interactions of the students and tutors with reference to their assigned spaces. The analysis was developed using the brief developed which was based on insights from participant observation and reflective practice and guided by the research motivation. This section was the focus of my published paper “Understanding social behaviors in the indoor environment: A complex network approach” (Williams, Burry, and Rao 2014b, A.3).

My first step was to understand the data that was collected and to verify that the data captured the behaviour that I sought. I designed a spatial visualisation that simulated the movement trends of the tag wearers and presented it as an animated video. I visually inspected the simulation result with a side-by-side comparison of animated movements from the captured time-lapse photos (Figure 13). I used this method to fine-tune the modelling parameters until I was satisfied with the outcome. I also used the simulated movement trend to generate tag positions for visualisation purposes. For more detail on the algorithm used, see Appendix B.1.

I investigated the underlying social network between the tagged individuals by modelling the tracking data as a dynamic social network. SNA centrality measures were applied to identify significant individuals who contributed to the structure of the social network. I interpreted the three SNA centrality measures as follows:

**Degree** is a measure of the direct interactions a person had. For example, a person with a low degree measure indicates this person worked more independently, whereas a person with high degree measure interacted more with others.

**Closeness** is a representation of the central-ness of a person. A person with a high closeness measure indicates that this person is more connected with the network, thus more likely to have a better knowledge of the status of the workshop.

**Betweenness** is a measure of one person’s criticalness on the overall reachability of the network. In our workshop context, a person with a high betweenness measure would indicate that this person performed more of the role of a messenger and acted as a bridge between two otherwise separate groups.

I developed several different graphical representations of the three measures that highlight the dynamics of the network (Figures 14,15,16,17).

Focused on exploring the relationship between people’s project assignment (“group”) and the choice of the interaction locations (see Spotlight on group assignment and spatial preference), I developed a series of group-centric data visualisations that demonstrated
6. Case Study 1: Discovery

<table>
<thead>
<tr>
<th>Spotlights on group assignment and spatial preference: Analyse the preferences of the individuals regarding their movement between locations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A</strong></td>
</tr>
<tr>
<td><strong>a</strong></td>
</tr>
<tr>
<td><strong>AA</strong></td>
</tr>
<tr>
<td><strong>aa</strong></td>
</tr>
<tr>
<td><strong>Ab</strong></td>
</tr>
<tr>
<td><strong>aB</strong></td>
</tr>
<tr>
<td><strong>ab</strong></td>
</tr>
</tbody>
</table>

Supplementary Figure 1: Group-location measures: Seven mobility analysis measures defined and demonstrated
6. Case Study 1: Discovery

Group-based mobility analysis measures:

- **Individual measures:**
  - **A, at home base:** This calculates how often one individual was at the locations assigned to his/her group.
  - **a, away:** This is opposite to *at home*; this calculates how often one individual was presented at the locations not assigned to his/her group.

- **In-group activity measures:**
  - **AA, at home meeting:** This calculates the in-group activity that occurred at locations assigned to the group. We assumed when two individuals from the same group met, they were conducting in-group activities.
  - **aa, away meeting:** This is the opposite to *at home meeting*, and is concerned with group activities that occurred at locations not assigned to the group.

- **Out-group activity measures:**
  - **Ab, receiving meeting:** While the individual was at home, how often he/she was visited by a member from another project.
  - **aB, visiting meeting:** This measures how often one individual visited the work areas of other projects and met with the members of other projects.
  - **ab, neutral meeting:** How often one individual met with people from another project at a location that was assigned to neither of them (neutral grounds).
Figure 13.: Visual inspection of the tracking data movement simulation. In this instance, the photo captured a scene at the start of the day where the participants were settling into the classroom. Two of the P2 (red) students have just arrived and can be seen greeting each other in the middle of the room.
Figure 14.: Comparing the changes in SNA centrality measures between the tagged individuals across the duration of the workshop using the temporal view. Top plot gave a clear view of when the spaces were active, the middle plot showed when closer collaboration occurred (start and end of the workshop), and the bottom plot revealed who seemed to act as connector between different clusters of people.
6. Case Study 1: Discovery

Figure 15.: Overview of the SNA centrality measures between the tagged individuals. P1, P2 and P3 were the project leaders and it was not surprising that they had higher directed interactions and central-ness compared to their students. This also revealed that I (P1) had the highest betweenness measure as I spent a large proportion of my time moving around the space checking my sensor deployment and talking to people. In this case, I might not be the most critical person in the workshop but I believe I would have the most up-to-date knowledge of what everyone was working on at any given time.
Figure 16.: The three SNA centrality measures presented in the spatial view (top) and interpolated into heat maps (bottom). With reference to the project space allocation shown in Figure 10, the visualisation shows that the groups seemed to have stayed in their assigned spaces. The heat map of the criticalness revealed that the bridging between clusters of people occurred in line with the corridor space between project groups.
6. Case Study 1: Discovery

Figure 17.: Two examples of the combined centrality visualisation. Mimicking a person for easier interpretation, for each node the “head” represents the degree, the “body” represents closeness and the “diamond” represents the betweenness centrality measures. The combined centrality view improves the perception of the behavioural differences between individual nodes.
## Spotlight on data reporting: Presenting curated visualisations for customised queries

The workshop coordinator wished to get a feeling of how the workshop had progressed as a whole. She was presented with Supplementary Figure 2.

“**Did the participants socialise much and mingle with other projects?**” Using combined out-group measures (Ab+aB+ab), through the temporal view (top) we could see that the workshop participants socialised regularly, and the spatial view (below) shows that interactions between groups were well distributed in the workshop space. This meant that the intention to fertilise informal cross-project discussions were successful.

“**Were neutral spaces required often for these occasions?**” Using the out-group neutral meeting measure (ab), we could see that the meetings between projects on “neutral grounds” occurred sparsely, and from the spatial view it occurred mostly at the centre of the workshop space around the coordinator’s desk. We suspected these meetings were facilitated by the group members to whom the spaces were assigned to (such as the coordinator at the coordinator’s desk).

“**How were the collaborations within the projects?**” Using the in-group meeting measures (AA+aa), we could see that the collaboration within the project occurred intensively in the first three days of the workshop. From the fourth day, Project 2 and 3 seem to have changed their working structure.

As the project leader of Project 1, I wished to see the work pattern of my project members. Supplementary Figure 3 shows the seven mobility measures for three members of Project 1. We could see that these three participants had similar in-group work pattern, and from comparing the out-group meeting measures it showed that I (P1) conducted most of the inter-project activities.
6. Case Study 1: Discovery

Supplementary Figure 2: Coordinator’s queries
6. Case Study 1: Discovery

Supplementary Figure 3: Project leader’s queries
6. Case Study 1: Discovery

the in-group and out-group activities between the different studio project groups. This set of measures was useful in comparing the working style between individuals and projects.

To apply the above analysis, I selected two targeted users (of Spotlight on a user-centric approach) to demonstrate how my approach could give targeted insight. Through curating the analysis and visualisations, I was able to provide the workshop coordinator with a set of visualisations to give them a feeling of how the workshop had progressed as a whole (Supplementary Figure 2). Similarly, Supplementary Figure 3 showed the project leader the work pattern of their project members.

6.4. In Reflection

I enjoyed myself in the full immersion of the intensive case study activities. It gave me an adrenaline rush that reminded me of the race to submission days at the design graduate school. There were so much happening and so many things to do that my reactions had sometimes become instinctive. I tried to keep an eye on the tracking system but my attention was always required elsewhere at short notice. The system failed a few times, due to a combination of software and hardware issues: unstable database that was not optimised to handle large data throughput and data requests from data analysis script, the script was not handling SQL requests cleanly, even the power board failed because I was powering too many devices from it, just to name a few failures. It was Murphy’s Law in demonstration: anything that can go wrong, will go wrong. I was equally frustrated but relieved that issues were revealed in this pilot study, my goal was to stress test the system and I was less concerned about the completeness of the data. My students with their expertise were very helpful in resolving many technical issues speedily. They were the proof that a collaborative and open approach is advantageous.

After the conclusion of the workshop studio, I was able to take stock and reflect on how the data collection worked and what could be improved for the next iteration.

I had difficulty in maintaining my role as an active participant in the workshop with my role as maintainer of the tracking system. I had a rudimentary system status report setup on a webpage hosted on the same RaspberryPi computer as the database that displayed the latest database entries. It was sufficient for showing that the tracking system was producing data and the database was operational, but during the workshop I wished it would also provide real time insight on the quality of the data, such as how many tags are currently in the space, what are their latest locations, and whether all the beacons are operational.
I also explored strategy to keep participants interested as a way to maintain participation and data quality. There were two parts to this: what to produce and how to present it to the participants. I had experimented with live data visualisation as part of the pilot case study, where I projected the visualisation on a large screen. I had many comments from people interested in observing where they were amongst all the data and interacting by moving about to trigger changes on the display.

The post-workshop analysis of data demonstrated that the data collected combined with the method of processing was of good quality. I was ready to expand the case study to a larger and more complex event.

6.5. What’s Next

Based on the insights and opportunities revealed by the pilot case study, I identified the following aspects that need to be tackled in the next phase of my research:

1. Repeat the pilot case study in a larger event
2. Improve the accuracy and stability of the tracking system
3. Build a cloud-based system to host data backup and live visualisations
4. Develop a set of visual reports that give participants live information and expand the live system maintenance report

This leads to the brief for next case study: deploy the IPMS in a large collaborative design event, improve the data collection process and expand the people analytics of my system.

6.6. Summary

This chapter presented the Discovery case study, my pilot case study on people interactions using WSN-based tracking. The prototype IPMS was successful in capturing quality data that revealed collaborative social behaviours.

The real world case study also revealed issues and ideas for further investigations. I planned a system upgrade to target a larger venue for the next case study. Notably, I will seek to explore ways to increase participant engagement as a means to improve data quality and to provide insights for expanding my analysis repertoire.
7. Case Study 2: Exploration

The *Exploration* case study is the second iteration of my people tracking case study. Taking lessons learned from the pilot study, I upgraded the IPMS to have improved data collection and remote database backup. I planned the study to have a similar collaborative design workshop context as the first one, so a comparison could be drawn between the findings of the two studies; but larger in terms of the venue and number of people involved, so I could collect a larger dataset. My focus for this case study was to expand my analysis repertoire.

Sections of this chapter have been previously published in:

- “A system for tracking and visualizing social interactions in a collaborative work environment” (Williams et al. 2015b, see Appendix A.4)
- “Graph mining indoor tracking data for social interaction analysis” (Williams, Burry, and Rao 2015a, see Appendix A.5)
- “Understanding face to face interactions in a collaborative setting: Methods and applications” (Williams, Burry, and Rao 2015b, see Appendix A.6)

7.1. Motivation

The motivation for this case study was to collect a more complex dataset so that I could further explore data modelling and analysis methods for collaborative behaviours.

Social networks exist everywhere in our daily life but the network is hidden and hard to comprehend by people that are unfamiliar with the concept. As demonstrated in case study *Discovery*, there is a huge potential for adopting the network approach with the tracking data. The field of network analysis is rich with theories and methods to model and explain dynamic behaviours in terms of individuals and their connections with each other. The research addresses the gap with respect to linking existing literature to practical real world case studies, especially how to communicate the findings to the case study stakeholders who are unfamiliar with both the concept and the field. For inspiration, I turned to self-reflection.
7. Case Study 2: Exploration

Figure 18.: The workspace (top) and layout (bottom).
The Context of the *Exploration* Case Study

**Activity:** An international design workshop

**Duration:** Five days

**People:** More than one hundred design professionals and students. The coordinators were event organisers and host representatives; the workshop consisted of ten projects, each led by project leaders who proposed the project and were assigned several participants. The tracking component of this case study focused on the coordinators and eight of the ten project groups.

**Space:** All of the project activities of the event were hosted in one building. The eight project groups of interest were situated on one floor, and the other two were on a landing and in a lobby loosely coupled to the main space. Of the eight, seven of these groups shared one large warehouse-like open space, where sections of the space were allocated to different groups. The remaining group was allocated an isolated meeting room off to the side. The coordinators also occupied a space near the warehouse.

**Data collected:** Five days of time-lapse photos and four days of people tracking data (fifty people) in the workshop spaces.

**Data collection method:** Complete participant observation and automated data collection. I was a project leader team member in the workshop for one of the eight projects.

**Note:** The technical setup of this case study was published in Williams et al. (2015b, A.4).

In the course of developing case study *Discovery*, I read many technical papers to build up my understanding of network analysis. Even with my background in data processing, I found the papers hard to follow and relied heavily on explanatory diagrams for comprehension. My major paper on the case study (Williams, Burry, and Rao 2014b, A.3) was presented in a design conference and I heavily utilised visual representation in the proceedings and my presentation. I received much positive feedback commenting on the effectiveness of the visualisation in explaining the unfamiliar concepts to the audience. This prompted me to explore a visual narrative approach in the second case study. This chapter explains my process.
7.2. Graphical Representations of Theoretical Concepts

7.2.1. Constructing Social Networks from Interpersonal Interactions

Person-to-person distance has been a common measure used to study social interactions. The classic proxemics theory of Edward Twitchell Hall (1966) categorised the four types of interactions (intimate, personal, social-consultive and public) by person-to-person distance.

From my observations of the collaborative design workshop, I interpreted proximity as a measure between two people’s statistical centres of activity within a set time period. As this is a measure between pairs of individuals, this measure can reveal how close members within a project group work together. I used a density plot to highlight the variation of interaction distances within a group. The distribution profile tells the story of the different types of project work. One sharp peak says that the group was working together on similar tasks, whereas two or more peaks say that the group work consisted of different tasks. It can be made more visually effective by referencing a group profile against the overall organisation profile and comparing different groups (Figure 19).

I upgraded the IPMS to version 2.0 (Figure 20) using the ZigBee’s expanded mode in which each data entry can be used to estimate the latest position of the tagged person. A proximity threshold was applied to all possible tag pairs to generate a list of interactions. A social interaction network was constructed with the network nodes representing tagged individuals and the network links representing the interactions. For a detailed technical description and comparison with the network project method used in the case study, please refer to Williams, Burry, and Rao (2015a, A.5).

The network representation is an effective tool to study the impact of individual interactions on the organisation in a holistic way. Automated network layout algorithms such as FDL use physical forces to simulate network node placement, the resulting network layouts are suitable for visual cognition of the overall structure.

Highlighting the properties of the network with known or calculated attributes can enhance the network visualisation. Visual cues such as colouring network nodes by their group attribute can show clustering of the group members and variance between the project groups’ work patterns; identifying member’s roles by node shape suggests a difference in leadership styles (Figure 21). Using SNA centrality measures to enhance graphical properties of the network helps with visual cognition of the individuals’ position within the overall network structure (Figure 22).
Figure 19.: Demonstrating the proximity variations between the projects. The line plots represent the density distribution of the in-group proximity pair for each of the eight project groups. The colour-shaded backgrounds represent all of the out-group proximity pairs that the project group participated in. The grey background represents the distribution of all of the calculated proximity pairs. Looking at the in-group proximity lines, we can see that the RN and DS groups have sharp narrow peaks close to the origin, this tells us these groups were physically static. This agrees with the on-site observation: RN and DS were computer-based design projects. Also observe the SG in-group proximity line has two peaks, this indicates the SG group had two modes of operation: our field notes confirm that during this data sample period select members of the group were tasked to man the project table and others left to visit other projects. Comparing the colour-shaded out-group proximity with the workshop result in grey, and focusing on the region near the group mean threshold, tells us the amount of distraction the group experienced and produced. For example, for FBR, its out-group proximity distribution closely matched with its in-group distribution. It indicates that for FBR members, within their work radius, it was as likely to encounter someone from a different project than one from their own.
7. Case Study 2: Exploration

Figure 20.: The hardware used in the second version of the indoor people monitoring system (IPMS). Left: the ZigBee system was in the expanded mode, which gave three beacons’ RSSI data per tag at a faster data rate. The participants were instructed to attach the tracking tag to their workshop name tag lanyards. Right: the time-lapse capture system was also upgraded to the RaspberryPi Camera Module which gave better photo resolutions.
Figure 21.: The interaction network that models the behaviour of the workshop compiled over the whole data collection period. The network layout was optimised using a FDL algorithm. The nodes were coloured by their project allocation, and the shape indicates the individuals’ roles: square representing the project leaders and circles representing the participants.
7. Case Study 2: Exploration

Figure 22.: Organisation interaction diagrams as recorded during one afternoon session of the workshop, using the degree (left), closeness (middle) and betweenness (right) measures represented as node sizes.
7.2.2. Group Behaviours

One distinct characteristic of my research is the focus on collaborative spaces. In this type of environment, all the occupants had existing associations with each other. In the first two case studies, the participants could be divided into groups by the projects they were assigned together. By isolating the data belonging to certain group members, I could focus on studying the inner group dynamics as the project progressed (Figure 23). Studies (Waber 2013, p59) have shown that at different stages of the creative process, a different interaction network structure should be encouraged: a star-like diverse network is suitable at the conceptual discovery stage where the project is collecting ideas; a cohesive network is good for the development stage where everyone works together towards the final goal.

Another insightful investigation is to study how the group interacted with the outside. Monitor group-to-group interactions to reveal the possibility of interference or opportunity for resource sharing (See Spotlight on identifying needs). Identify group to wider organisation out-reaches to help determine an individual needs pattern for specialist resources or expertise (Figure 24). The group cohesion dynamic mentioned above also extends to the group-to-organisation interface, a shift in out-group activity dynamic may have been caused by a change in the in-group work mode, or vice versa.

7.2.3. Building the Narrative

As I have discussed in the Discovery case study, indoor people tracking technologies are highly volatile and data collected using such a system is context specific. It is important to keep in mind the relative and entangled nature of network data, network representation and analysis. The strength of a network is in the connection of the individuals, which is shaped by the context they are in. The findings from those data should not be discussed in isolation, but must be considered within the context in which they were captured. Those are in the form of supplementary contextual data such as floor plans, organisational diagram, project description and schedule, as well as automated contextual data such as ambient sound level and other environmental conditions.

One advantage of a user-centric approach is that the targeted viewers are the people presented in the data or associated with the organisation, who have existing contextual knowledge that should be tapped into. This indicates to present data findings in ways that viewers can orientate themselves, so that they can compare the findings with their contextualised experience. In practice, I used temporal and spatial plots which are familiar to the viewer so they could go “this is Tuesday afternoon and we had a meeting”
7. Case Study 2: Exploration

Figure 23.: In-group behaviours of the eight project groups as recorded during the afternoon session of Day 2 of the workshop. The node shape indicates the individuals’ role: square represented the project leaders and circles represented the participants. From the variations in the weight of the interactions between project group members, we can observe sub groups have formed in the projects.

Figure 24.: Out-group behaviours of each of the project groups as seen from the overall organisation interaction diagram, with the interaction participants highlighted. Interesting observation comparing SG and FBR: although SG had conducted more in-group interactions during this workshop session, it has met up with a large proportion of the workshop participants; whereas FBR member’s out-group interactions were less frequent and more selective.
7. Case Study 2: Exploration

**Spotlight on identifying needs: With the help of network analysis**

Project SE (orange, bottom left diagram) was assigned two spaces, one in the building atrium, one in the right end of the long open studio space as seen in the floor plan. This meant there was regular traffic between these two spaces, directly impacting the operation of RN (yellow, bottom right diagram). Before long, two movable screens were put in place to provide partition between RN’s space and SE’s space (Supplementary Figure 5). In this case, the Supplementary Figure 4 spatial heat maps clearly demonstrate the disadvantaged situation of RN: they have the smallest in-group heat map because their in-group interaction was flooded by the distractions from their neighbours.

In comparison, FBR was also centrally located with possible distractions coming from three sides, but as seen in Supplementary Figure 6, they managed more undisturbed in-group interactions. This was because FBR was allocated a wide space, which acted as buffer to protect the project from unintentional distractions.

Based on these observations and interpretations it is recommended that future workshop space allocation consider traffic distractions around projects and allocate additional buffer spaces to projects that may be affected.

Supplementary Figure 4: Spatial interaction maps. Top: workshop overall; left: SE; right: RN
7. Case Study 2: Exploration

Supplementary Figure 5: Photo evidence of physical intervention done by RN

Supplementary Figure 6: Spatial interaction map of FBR
or “that’s the 3D printer station, I remember spending lots of time there getting my prototype printed”. Graphical features help to get orientated with abstract network visualisations.

Building a narrative assists viewers in orientation and navigation through the data. In Discovery, I used an animated spatial plot to present dynamic data as people movement (Figure 13) and curated data findings to two targeted users with expected contextual knowledge (see Spotlight on Discovery customised queries). In Exploration, I further explored strategies for a narrative approach in data presentation, focusing on communicating dynamic network properties using temporal storyboard and group-wise comparison.

Another important narrative is the data processing process. I went through a data exploration process from my first contact with the complete tracking dataset, through iterative application analysis and visualisation, gradually building comprehension of what had been captured in the data. My experience led from idea to the hypothesis that presenting data findings in an exploration-like narrative set up makes the findings easier to be comprehended by viewers. I explored this narrative approach in this case study as a way to explain unfamiliar complex theory to my readers.

Rather than expecting the viewer to take a leap of faith with the final findings, it helps to convince of the validity of the methods and the results if the process is explained. My data exploration revealed opportunities for insight within the intermediate analysis process: people proximity insight from the data modelling process, organisation dynamics from the complete network analysis, and group interaction dynamics from the sub-network visualisation. By moving between visualisations, the viewer builds a multifaceted comprehension of the behaviours captured by the data.

7.3. Evaluation

The aim of this case study was to develop the analysis of the tracking data, exploring ways to unveil and convey insights for the targeted users. The evaluation will focus on effectiveness of the behaviour modelling on capturing the interactions of interest, as represented through the data visualisations. I will present the evaluation in two aspects: the adaptive behaviour modelling methods and the multi-resolution network data visualisations.
7.3.1. Adaptive Behaviour Modelling

The extended tracking system was used in this case study. As discussed in Spotlight on wireless sensor network (WSN) based people tracking, the extended data mode can be easily converted into the basic mode. I have designed two behaviour models that correspond to the two data modes.

The signal processing based behaviour model (SP) uses the extended data mode to process the tag data independently before performing association analysis to convert it into tag-tag pairwise links for further SNA; the complex network behaviour model (CN) uses only the basic mode data and applies bipartite network project to extract tag-tag unipartite network for analysis. Both models are adaptable with multiple parameters: the duration, proximity and activeness of the interaction are interpreted as parameters to fine-tune the models.

The performance of the two models was evaluated with an hour-long sample data using comparative and ground truth evaluation methods. The SP approach performed better on all measures. Considering CN approach utilised only one reference beacon ID and none of the RSSI values, whereas the SP approach required three reference beacon data pairs (both ID and RSSI) per tag entry, the merit of using the CN approach (such as lower data storage and processing requirements, simpler data collection system) should still be considered. For more information please refer to Williams, Burry, and Rao (2015a, A.5).

7.3.2. Incorporating Context at Multiple Network Dimensions

The FDL (demonstrated in Figure 21) gives us a good visual overview of the strategic importance of each individual’s contribution to the overall workshop interactions. We can highlight different behaviors by applying the three aforementioned social network centrality measures to the interaction network. Figure 22 demonstrates the behaviours of individuals in the workshop during an afternoon session (Day 2), using the automated network layout node placement with the node size representing the centrality measure scores.

A cohesive group interaction network represents healthy collaborative teamwork. This is best represented graphically by constructing an in-group interaction network for each of the project groups by extracting the network links that connect the nodes belonging to the same group. A circular node layout was used, as it is best for presenting the interaction patterns. The node shape identifies the individual’s role; node size represents the number of interactions that the individual had participated in. A fully cohesive
network is one where balanced network links exist between all of its team members, and is more common in a facilitated meeting; for project work a biased interaction network was expected, as shown in Figure 23. My field notes and supplementary data confirmed that during the represented time sample, there were distributions of the tasks to form sub-groups within projects.

In a collaborative co-located work environment, such as the one from the case study workshop, the amount and diversity of out-group activity can be both a blessing and a curse: too much interaction between different groups distracts the team from working on its own projects, but not enough out-group interaction most likely shows that the project has not explored the skillsets and expertise from people outside the project. As seen in Figure 25, project PM was more isolated and had limited interactions with other projects. Interestingly, both the ST (teal) and SG (purple) groups were relatively centrally located but their members did not interact much with other project groups either.

It is worth flagging when a project group was shown to be involved in a large amount of out-group interactions. This calls for further investigation to identify with whom (Figure 24) and where those interactions occurred (Supplementary Figure 4), and if more contextual information is available, whether the interaction level was a distraction to the groups involved. In the case of the neighbouring projects SE and RN, the interaction was disruptive and a few screens were requested to construct a barrier between the two project spaces (see Spotlight on identifying needs).

Interaction dynamics are difficult to quantify and measure. Presenting the organisation-wide analysis result alongside results from individual groups (such as Figure 25 and Figure 4) helps the viewer to understand the variation and cause of the interactions. Organisation-wide dynamics can also be perceived through comparing visualisation across the time sample. To this end, I divided the data into timed sample blocks: each day’s data was separated into morning (8 am to 1 pm), afternoon (1 pm to 6 pm) and evening (6pm to 8am of the next day), resulting in twelve sample blocks. I then constructed an interaction network for each of the sample blocks and generated the organisation interaction diagram based on the degree centrality measure (Figure 26) and the interaction spatial map (Figure 27). As we can see from the twelve sequential network diagrams (Figure 26), as expected, the interactions that occurred showed high group clustering preference, but of more interest to us is that through these diagrams we can also observe variations between the sample time periods: the interactions became more group orientated as time progressed towards the conclusions of the workshop (on Day 3). This is vastly different from the interactions that occurred during the exhibition (evening of
Figure 25.: Pie chart comparing the proportion of in-group and out-group activities across the workshop groups.
Day 4) when people mingled while visiting each other’s project exhibit.

7.4. In Reflection

This case study was a perfect step up from Discovery as a system stress test and stimuli for expanding my people interaction analytics.

Compared with Discovery where everything was contained in one room, Exploration occupied a whole floor of a large building. With more than one hundred attendees and many concurrent intensive project works, it was beyond the capacity of any one person to keep track of everything. The system stood up to the test, with only minor data blackouts. On the first night, the special power down setting in the room cut power to the RaspberryPi unit and corrupted the local database, but thanks to the automated remote database back up I only lost few minutes of the data. Every so often beacon units got unplugged unintentionally, but with the automatic mesh characteristic of the ZigBee network this did not affect rest of the system and it recovered as soon as the unit was powered back on. The live data visualisations were effective as a system monitoring interface, which I used to identify beacon and database outage.

The energy level at the workshop was intense, each project jamming a whole development cycle into the limited hours of four days. There were activities around digital modelling, 3D printing, large scale fabrication, and digital projection to name a few. As mentioned above, goals of the workshop were to provide an environment for attendees to participate in one of the allocated projects, as well as to stimulate idea exchange and foster new personal connections between the attendees. For many people this was a constant balancing act, “I really wanted to see the other projects, but I needed to get this done first.” An example is PM (coloured red), who had requested an isolated space to provide a stable test environment for its experiments. From Figure 26, I could see the impact this spatial segmentation on the workshop-wide interaction network: the PM members had formed a close-knit cluster with little interaction with others. Some relief from this isolation can be seen on the afternoons of Day 1 and Day 2, when the workshop had organised presentations open to everyone, although it is clear that this temporal integration had little long-term impact. A possible function of an IPMS could be highlighting events and the arrival of people, so time-rushed people know when to “just pop in for a few minutes”. Along the same lines, it would also be useful for people to check if the facilities are free and when are the likely down times. I also had many requests for people wanting to locate certain individuals. Although this was not possible due to the privacy agreement set in this case study, this is a feature that could be con-
7. Case Study 2: Exploration

Figure 26.: The organisational-wide interaction diagrams, individual level interaction intensity is emphasised by the size of the individual nodes (degree centrality). Node colour represents group associations.
7. Case Study 2: Exploration

Figure 27.: The organisation-wide spatial interaction maps showing the locations of in-group interactions (coloured pink) and out-group interactions (black), as recorded by the four days of tracking data. Presented spatially and sequentially, we can clearly observe the change in the spatial usage of the workshop as the workshop progressed.
Considered in future applications. For example, a user interface provide people the ability indicate temporary “public” visibility, with this project leaders or individuals could be away running errands and be located if required.

A group that would greatly benefit from the location data was SG, the team of workshop organisers. They were constantly run off their feet, stretched to every corner of the physical space catering to the needs of all of the project groups. Within the team they allocated tasks, people had to visit the help desk multiple times to catch one specific person. For the SG team themselves, they were also interested to know with who and where they had interacted so they could make adjustments to scheduling and respond to demand trends. I managed to engage one of them for a quick chat and showed him some of the preliminary visualisations. He was very excited to see his own data (Figure 28), he asked for a copy and straight way shared to everyone using social media. I gave him the web link to the live visualisations, and he made many screen grabs and included it as part of the final presentation to all the participants and industry invitees. Through his actions, my tracking project received much publicity, both during and after the event. This also landed me the contact for my third case study.

7.5. What’s Next

This case study has demonstrated the capability of the IPMS to reliably track more than fifty people across a large indoor space. Post-collection analysis development revealed many promising real time applications to collaborative workplaces. I sought an opportunity to deploy my research in an industry setting.

There are possible real time insights that my system can support:

- For optimal organisation performance, interaction patterns should match the organisation structure and task dependencies (Pentland 2014). A narrative constructed with a set of visualisations (shown in Section 7.2.3) allows organisers to identify and encourage positive interactions as well as implement early intervention to remove distractions.

- Ongoing spatial usage evaluation is required to ensure the compatibility between the spatial layout and the intended interactions. The analytic system I developed can automatically produce historic reports of the space usage. This information is valuable for the active management of workplaces (Haynes 2008). For example, the outcomes from the interaction analysis can be used to flag spaces that require activation and recommend reconfiguration of employee desk allocation.
Figure 28.: One of the workshop organisers’ movement in ten minutes (top) and all the places he had visited (bottom).
7. Case Study 2: Exploration

- A project group can use the in-group interaction diagram (Figure 23) to manage the communications in the group. The members can increase their awareness of the dynamic of the in-group interactions through monitoring the real time report of the in-group interactions. This should encourage a more balanced contribution of the members, build trust and integration within the group and contribute to better overall performance. The out-group interaction diagram (Figure 24) is useful for identifying expertise from the organisation to be included in the project.

- On a higher level, company management can also gain insights from interaction analysis. From individuals, analysis such as degree and betweenness centrality measures (Figure 22) can flag persons and relationships that may require additional support or to be encouraged through reward. A combination of face-to-face in-group engagement and out-group exploration is indicative of the creativity and productivity level of a project group (Pentland 2014). Although the context of each project can be unique, the availability of live and historic interaction data allows the managers to have close engagement with the project groups to find the winning formula for best performance.

This leads to the brief for the next case study: deploy the IPMS in an industry workplace setting and develop people analytics to support the daily business operation in the office.

7.6. Summary

In this chapter I have demonstrated the capability of the data modelling and analytics to represent people behaviours in a large international design workshop. By focusing on visual presentations, the analysis methods were able to uncover insightful engagement patterns that informed us of a range of dynamic behaviours including participant engagements, project group collaboration and overall workshop dynamic. Specific to this case study, the analysis was able to identify scenarios of interest and provide recommendations for the planning of future events.

The system and methods presented here have applications in increasing the program compatibility of office layout designs, supporting active workspace management for efficient facility usage, as well as improving group performance at both an individual and a management level. This became the focus of the final case study where I sought the partnership of an industry organisation to examine the road test as the summation of my research in everyday professional practice.
8. Case Study 3: Deployment

This case study was the culmination of my PhD research, where all of my research explorations came together to inform a deployable package that I road tested in a professional industry context. I followed my user-centric approach to conduct my participant engagement process; it guided my selection and development of analysis methods. A significant validation of the work was that, through our close engagement, the host organisation was convinced of the value and significant opportunities of people tracking and analytics, such that they established a people tracking research and development portfolio based on this work.

8.1. Motivation

The aim of this research is to develop a user-centric approach to establish active people tracking in workplaces. Through my associated work with my research group SIAL, I had access to design workshops for my first two case studies. They were short self-contained events, and I was involved in the organising and delivery of the workshop activities. The case studies benefited greatly from my insider point of view, as I was able to get detailed plans of the events, have earlier access to the venue and establish relationships with the organisers, to name a few perks. The two case studies were successful but they showed greater potential in many industrial applications. At the conclusion of Exploration I was confident in the stability of the system and my experience in the participant relations that I felt I was ready to take on a real world industry case study.

The success of the two earlier case studies helped me connect with industry and professional design practices. I was invited to present my research on the application of indoor people tracking to a design-consulting firm, who at that time were in the process of furnishing their new office and were interested in hearing more on people tracking technologies for spatial design applications. After my presentation, we discussed opportunities to collaborate on a research and development project on people tracking for post-occupancy evaluation. They invited me to come back when they had occupied the new space and spend a few weeks in the office with them.
8. Case Study 3: Deployment

Figure 29.: The workspace (top) and layout (bottom).
The Context of the Deployment Case Study

**Activity:** Daily operation within a consulting company office

**Duration:** Seven weeks

**People:** Company employees across all management levels

**Space:** Flexible open-plan with mixed-use zoning configuration

**Data collected:** Seven weeks of people tracking data (thirty-eight people) and time-lapse photos (eight cameras). Corresponding seven weeks of ERP data listing the project the employees were working on and how many hours the task was allocated for.

**Data collection method:** Passive participant observation for the first three weeks and automated data collection. Three focus group meetings were conducted. A questionnaire was distributed at the conclusion of the data experiment.

The company was interested in developing their own IPMS and application. They selected an alternative Bluetooth low energy (BLE) beacon-based tracking technology, which allows smart-phones to use their Bluetooth® functionality to orientate themselves in a space that has been fitted out with BLE beacons. Although we were using different IPMS to collect data, they were interested to learn from my people analytic experiences. We agreed that our collaboration would benefit greatly if I was on-site; my physical presence would mean that we could have a closer knowledge transfer. For me, this close relationship was consistent with my findings for a successful deployment from earlier case studies, so I was excited for the chance to test my theories within a professional practice context.

### 8.2. Setting Up for Success

Successful relationships are build on trust between the parties. Deploying tracking sensors in a workplace to collect meaningful data from employees required the participants to place a very high level of trust in the people handling the data. This trust relationship was required on multiple levels: from the organisation management to me, from the employees to me, and from the employees to their organisation management. I was very aware of the potential to cause harm if the data was mishandled. This demands a level of sensitivity and a carefully planned engagement strategy to minimise the risk and to convince people that their trust was not misplaced.

I have taken the approach of being transparent and engaging with my participants (both the employees and the management) as a strategy to gain trust and maintain
participation. Being open and truthful of the project aim and providing live data visualisations to show what data had been collected and how the data was being used helped me to gain trust from the participants. Being open to suggestions for additional analysis that provided insights to the participants made them feel that their ongoing participation was of value to the research.

8.2.1. Building the Foundations

It was fortunate that the host organisation had a professional interest in the project. They also had an open culture in the company that all employees, regardless of role and seniority, were encouraged to participate in regular company-wide presentations. Those presentations allowed attendees to be exposed to discussions on the developments within the company. My initial presentation was done in one of them. This allowed everyone to be presented the same information, an open opportunity to ask questions, and observe the initial negotiations between the CEO and I that kick-started the project.

At that time, the company was investigating application of indoor tracking technologies as a new business venture. They were interested to use their new office as a test bed. A research and development team was formed: I was partnering two of the staff that were developing an indoor tracking application based on the BLE tracking technology. We built our collaborative relationship on a commitment of knowledge transfer. Through interacting with me in the project, my two collaborators wanted to learn more about the indoor tracking technologies and the types of analytics available. I would learn from their technical expertise and insights from working in the building and construction industry, as well as their personal experience from working in the company.

8.2.2. Participant Engagement

My host organisation had an active presence in the case study. I was partnered with staff from the company in the aforementioned collaborative project; we had frequent and ongoing technical discussions. One of my project partners was my point of contact within the organisation.

Together with my collaborators, we introduced the project to the whole organisation during one of the company’s organisation-wide presentation sessions. I presented the ZigBee tracking component of the project, described the terms of the case study and answered questions from the employees. After the presentation I collected signed participant agreements (they were emailed out prior to the presentation) and distributed tracking tags.
8. Case Study 3: Deployment

I was physically present within the organisation for the first three weeks of the data collection period. During this time I was provided with a desk space in the office, which I occupied during the regular office hours. The in-office residency allowed me to observe and engage with the people in the office.

Three focus group meetings were conducted, where I presented analysis progress to tracking study participants and other interested parties, and discussed user experiences and potential applications of this technology.

I engaged office employees in informal discussions during their breaks and I was invited to attend lunchtime organisation-wide presentations. Many of the participants had a professional interest in the project, offering suggestions that I incorporated into the project.

I took an initiative to demonstrate the capability of data collection system by analysing one of the office social activities. This gamification of the study was successful at drawing people’s attention to the project, especially to the live visualisations. I prepared the system to be fully automated by the end of my four weeks in office residency. I handed partial access to the system over to the technical staff, giving them instructions on how to maintain the system until I returned to remove my installation after three weeks of absence.

At the conclusion of the data collection, I negotiated access to the company’s ERP data for the corresponding time period. With these data, I studied whether the people’s physical behaviour varied with their job assignment.

8.2.3. Targeted People Analytics

From my previous case studies I had constructed a large set of people analytic methods for modelling behaviour and extracting insights. The goal of this case study was not to design new methods but to explore ways to target my existing repertoire for the new context.

I used an explorative approach, focused on constructing an appropriate live data analysis pipeline, selecting insightful data outputs, designing easy to read visualisations and curating them into a webpage layout.

My initial design was based on my experience with the previous case studies, which I transformed into a live processing analytics system. I continuously worked on this system while I was in residence, based on my observations and my interactions with the people in the office. I was provided with a list of employee job titles and department (business unit) assignments, which I used as individuals’ attributes for analysis and visualisation.
8. Case Study 3: Deployment

The online people analytic visualisations I designed for this case study are summarised below:

**Spatial Plots:**
- The spatial layout overlaid on the floor space was set up to give a quick overview of where everyone was, especially for my participants who were building consulting professionals.
- I also derived a movement trend plot that showed individual’s general movement direction in the last ten minutes.

**Temporal Plots:** I used this to indicate the activeness level of the individual or department.

**Network visualisation:**
- A direct bipartite network that visualised people’s current locations was used to highlight space utilisation in the office.
- A proximity-based interaction network showed possible face-to-face interactions that occurred throughout the day.
- A selectively triggered interaction network model was used to isolate interactions that involved one or both parties that have recently changed locations. This was designed to highlight the individuals who were approached/interrupted in their work most frequently by colleagues.

The visualisations were curated into a webpage, each accompanied by a short explanatory description. The webpage was publicly assessable. Data was only identified by tag ID and the wearer’s department assignment to protect the privacy of the participants.

8.3. Evaluation

The focus of this case study was on *deployment*: negotiating the premise of the tracking exercise with the management; building and maintaining positive relationships with the participants; and designing targeted people analytics.

8.3.1. The Set Up

The case study was successfully conducted; one essential contribution was the solid trust relationship I had with the host that was built on clear understanding and the willingness to negotiate.

Together with my supervisors we had regular videoconferences with my contacts in the host organisation in the months leading to my time spent in the office to work out
8. Case Study 3: Deployment

the brief of the collaboration. These discussions were helpful in setting the limits of my engagement as well as the usage of generated data and intellectual property (IP). I relied heavily on my ethical application process with my institution to draw up written agreements with the host organisation. I prepared a version for the participants that was distributed to them prior to my arrival. The formality set a strong foundation for trust. Once written agreement was approved by the senior management from both sides we began a more fluid exchange of information, sharing technical expertise and detailed site data. This further supported my positive approach to the ethical application process to aid the preparation of case studies.

It was understood that this was an explorative experience for everyone involved. The host organisation had purchased a few Bluetooth beacons (Estimote BLE Proximity Beacons). The technical project partner, who was experienced with building computer interfaces for smart devices, had played around with the demon software with a set up in his small office. Having used my tracking system for two overseas case studies, I have perfected my physical set up into a neatly packed suitcase with everything under 23kg ready to be taken on a plane to anywhere. Before I departed I set up a cloud-based computer to back up the database, run analysis scripts and host the web-based visualisation.

We had planned to conduct most of the technical analytical development once everyone had assembled on-site. I had the base visualisation set up so I could conduct installation and calibration, and code ready for the other in-depth analysis. I wished to have a chance to observe the daily operation of the office and discussed ideas with my project partners before putting together the visualisation for the participants. I was especially excited by the opportunity to work with my project partners, who were well known in the industry for their innovative thinking and technical achievements.

Our technical developments were distinct: my project partners worked on a BLE solution with a focus on spatial usage application, I worked with my ZigBee system and focused on social interaction analytics. This did not impede a fertile collaborative relationship that supported conceptual and technical discussions.

Through this set up I was presented with greater insights on the organisation, and our successful partnership convinced the host to entrust me with their company’s sensitive ERP data for further analysis post data collection. The usage of this data was set out in written agreements and I sought ethics approval from my university through an amendment process. This demonstrated the opportunities of an open-minded explorative approach supported by a flexible administrative process.
8.3.2. Analytics

The aim of the analytics I implemented for this case study was to highlight opportunities for an IPMS to provide insights. The inspirations came from my direct observations of the company’s work culture, through interacting with my project partners and other employees. I did not set out to present an all-encompassing solution that replaced existing office practice, rather I revealed insights that could be used to support the daily operations.

Advantages of my system are its capability to independently collect and analyse large quantities of data in real time. I set up scheduled scripts on the cloud-based computer to process incoming data and generate visualisations. The webpage hosted on the same computer displayed the visualisations accompanied by a short description. Through this platform, my participants were able to access the latest insights generated by their data. Here is a selection of the analytics that were used during this case study.

Spatial Overview

Two spatial overview visualisations showed the current activities in the office and the general movement of the people. They were the starting point for someone to orientate themselves with the data and were visually straightforward, especially for my participants who were building industry professionals. The tags’ unique tag IDs were not made public, I used them to identify the individuals’ last position estimate for the participants to check. Icons or names (if consents were given) could easily replace the tag IDs to further customise the graphics. Another application for these visualisations is to see if the attendees have arrived in the time leading up to a meeting.

Department as Group

A major analytical decision I had to make was to determine my interpretation of group for this context. I chose to use staffs’ department assignment to separate the participants into distinct groups. It was expected that the behaviour would be distinct between the departments due to the different types of work involved in each. The Run staff were always on their feet moving about supporting the daily operation of the office, the Project staff were the design consultants that worked in small collaborative teams that met frequently, the Software staff was also team-based but their work was all computer-based.

This was indicative in the proximity density visualisation (Figure 32) that highlighted the difference in work interaction patterns across the different departments.
8. Case Study 3: Deployment

Figure 30.: The location visualisation plots the latest ten minutes of estimated tag positions. This visualisation is useful to give an overview of where the activities are in the room, with emphasis on the departments. In the example here the Project staff (orange) were in two clusters (one in a conference room and another at the bottom right of the space), other departments’ presence were mostly around the desks; in comparison the presence of the Run (support, in blue) staff was distributed throughout the office.

Figure 31.: The latest movement visualisation shows the general movement of the tags in the last ten minutes. Dividing data into two five minutes blocks, an “activity centre” was calculated for each tag based on the tag’s estimated positions from that time block. The shift in activity centres over the two time blocks were plotted. In the example here, we can see that every one except a Run staff were fairly stationary across the ten minutes.
8. Case Study 3: Deployment

I designed an activity-level visualisation (Figure 33) that highlighted the differences in mobility dynamics across the different departments throughout the day. This timeline was interesting for staff to see the activity level within their own department and compared with other departments. It could also be useful for managers to refer to for planning and scheduling.

**Network**

The proximity approach developed in *Exploration* was used to build the DSINM. Network links were time-logged and accumulated over the course of the day. Interactions between all participants were visualised in a daily-accumulated organisation-wide graph (Figure 34) as well as extracted inter-departmental interactions (Figure 35).

One limitation of using the proximity-based DSINM to represent collaborative interaction is that it assumes proximity gives rise to interaction. After being close to each other for a period of time, it is more likely that these two people would be more aware of each other than of another person at the other side of the room. This might be the case when the seating plan relates to the collaborative relationship, or people had total freedom to choose where to work and who to sit with, as was the case with the workshop scenario in the first two case studies.

Note that with the DSINM, links were determined from the physical proximity of people’s estimated centres of activity only. This does not guarantee that the two people involved had a face-to-face interaction such as a conversation; they could easily be just sitting nearby and working independently. I observed that many staff used headphones in the office to play music and block out sounds from others.

In response to this, I explored intended interactions by combining the proximity data with individual’s calculated mobility to filter for interactions that involved one or both parties to have physically moved prior to contact. I used this approach to investigate my observations on work continuity: some people were more frequently interrupted with people popping by to ask a short question or get quick confirmation; and some people seemed to be always engaged in meetings. I have had managers commenting that they were always chased for questions that they go into hiding to get work done. In Figure 36 we can clearly see from the active-to-static plot that a few staff were being disturbed more than others, the active-active plot could be used to identify possible desk assignment rearrangement to support frequently collaborating pairs.
8. Case Study 3: Deployment

8.3.3. Participant Engagement Strategy

The ZigBee system had the advantage that it limited data collection to tracking wearable sensors. Unlike the BLE system developed by my project partner, my system decoupled participation from personal devices. This gave people more control over their participation and privacy. It also meant that I did not need to exclude people based on their personal device ownership and status. The partnering BLE development was affected because the development was Apple® iOS based and required the latest updates; this hurdle barred a large proportion of the staff.

Being situated within the daily operations allowed me to capture opportunities to further engage with my participants. I conducted frequent participant engagement activities, especially at the start of the data collection period. The collaborative project organised several focus group meetings, inviting a small group of staff from the office to hear the progress with the project and share their thoughts. Throughout the day I was also informally approached to answer questions and hear suggestions on possible analysis and applications. At the onset of the project I set up a basic online visualisation that showed the latest location of the tags. This stimulated interesting discussion threads, especially one surrounding the behaviour of the company’s resident pet dog that was also being tagged. Based on the feedback from the participants, I was constantly improving the graphics of existing visualisations and developing new analytic measures.

One common feedback was that compared with other forms of data visualisations, network visualisation was harder to comprehend due to the abstract concept it represents. When I first showed people the network visualisations I got comments like “it looks interesting but what does it mean?” I helped the participants with additional descriptions and examples. Once the initial hurdle was overcome, people were able to quickly extrapolate their own interpretations: one staff noticed from the organisation-wide interaction network that there was an individual that was isolated from the network; this person then rallied others to interact with this person more often (see Spotlight on user feedback). Another effective source of inspiration comes from unscheduled once-off social events. I was more experimental and playful with these visualisations, and I had great responses from the participants (see Spotlight on capturing the moment).

Through these exchanges I reminded people to carry their tags in a friendly way, people quickly got used to their role as participants. This was reflected in much of the post data collection participant feedback: all the people that responded to the questionnaire stated that despite the fact that they were being observed/recorded, it did not affect how they behaved in the office after an initial period; it “became normal” and they simply “forgot that it was on most of the time”.

101
8. Case Study 3: Deployment

Spotlight on user feedback: Examples

I received much feedback from the staff, commenting on how they perceived the visualisation. One positive change caused by the visualisation was that people noticed from the organisation-wide interaction network that there were individuals who were socially isolated (such as the one in Figure 34); people began to make conscious decisions to visit these individuals at their desks and invited them to breaks.

The visualisations also stemmed a discussion on healthy working patterns. Looking at the spatial plot of the movement behaviour, the Software people joked that they were always in the corner and never got off their seats, whereas the Run staff were always on their feet (for example Figure 30). I took this idea and derived the daily activity rank plot (Figure 7), which confirmed that the Run staff indeed travelled the most.

Supplementary Figure 7: Daily activity rank plot.
Figure 32.: The proximity density visualisations highlighted the difference in work interaction patterns across the departments. This is taken from the same time sample as Figures 30 and 31. The plot shows two peaks in the Projects’ data; it picked up that the Project staff were operating in two different modes.
Figure 33.: For activeness level, I looked at the area travelled by each tag-wearing person, calculated per every five minutes block, plotted as a temporal graph and grouped data into departments. In the example here, we can see there was activity at the start and end of the day, periods of quiet time in the morning and afternoon, and a few staff worked late into the night. There were two synchronised activity peaks around 1pm to 2pm, this coincided with people arriving and departing at one of the regular lunchtime organisation-wide meetings.
Figure 34.: The accumulated daily interaction network visualisation identified senior staff with square nodes and emphasised people with more links with larger node sizes.
8. Case Study 3: Deployment

Figure 35.: Looking at the daily interactions within each department.

Figure 36.: Movement triggered interactions. By filtering data based on movement, we identify individuals that had a more interrupted work environment.
## Spotlight on capturing the moment: The impromptu Gang War

The company had an active office culture, and I witnessed many self-organised social events; one especially of interest was the in-office “gang war”. Two groups of staff, one situated in the south-west part of the office and the other in the east corner, seemingly start shooting each other with nerf guns at random times during the week. They were amusing events to witness, one team would sneak around the conference rooms and coordinate attacks from both ends, whereas the others ducked around desks and computer monitors to fire back.

The matches were a source of great excitement to the whole office, a sure way to release mental stress or physical strain at the end of a long day. I watched a few of these matches play out while I was in the office, and thought it would be interesting to visualise their strategy using the tracking data.

I approached the groups to suggest to do some strategy visualisation for them. They were very interested and gave me the list of the team members and time period of their latest “clash”. I extracted the corresponding data and generated a frame-by-frame break down of the teams’ movements (Supplementary Figure 8).

The resulting visualisations generated much talk in the office. This sparked a fascinating email chain through the office where the teams argued about who had gained advantage and won. It also stimulated discussions on other possible applications of the tracking system.

Overall, this simple intervention provided sustained positive interest in the tracking system. It gave the participants a clearer idea of the data collected and what it can reveal. People became more inquisitive about the project, frequently checked their individual data visualisation page and consciously carried the tags with them as they moved about (Supplementary Figure 9).
8. Case Study 3: Deployment

Supplementary Figure 8: “Gang war” tactics visualised
Supplementary Figure 9: This impromptu engagement had positive long-term effect on the tag wear rate in the office.
8. Case Study 3: Deployment

The insight I presented to my participants gave them a positive incentive to continue participating. The sense of involvement and ownership also built trust and encouraged good tag-wearing practice, and thus better data.

After three weeks of residency, I left the system to be maintained by the organisation staff for the remainder of the data collection period. I gave the IT staff detailed instruction on the configuration and debugging scenarios, and the administration staff a daily process to check and remind participants to take their tags with them to and from work. This was sufficient to keep the data collection system operating in my absence. The staff reported that they enjoyed the responsibilities; they took it on themselves to send out daily reminders for the people to carry their tracking tags.

8.4. In Reflection

This case study is distinct from the two previous case studies I conducted in many ways. Firstly it was an industry context, which I did not have much exposure to before. I recognised my relative inexperience in the current context; thus reflective practice played a lesser role. I relied on participant observation and informal interviews for data analysis ideas and for feedback. I utilised the collaborative relationship to question my project partners on every aspect of their work practice. When I chanced upon employees in social conversation I would quiz them on their work style. The incidental but highly insightful input had come from people who curiously popped by my desk after work. They were often happy to sit down for a long chat and review my work in progress. With my code snippets handy, I would quickly implement the recommendations and get instant feedback.

The second point of difference is the complex nature of the collaboration in operation at the office. I observed from the planning documentation that the job assignment within the company was complex, with project teams composed of staff from different departments and staff multitasked across different projects (see Figure 37). Projects also have different durations; work start, end or change team composition with a fluidity that was difficult to comprehend by an outsider like me. Early analytics showed opportunities (Figure 38) but I quickly realised expanding my DSINM to represent the dynamic nature of the staff’s workload and project team composition was beyond the scope of this research. I was not able to come up with a categorisation method to divide the participants into collaborative groups similar to the groups in the earlier case studies.

In response to this, I turned to use people’s department assignment as the group attribute in organisation-wide analysis and visualisation. This was effective for visual
Figure 37.: Early explorations of project network. The ERP data registered 38 projects over the five weeks. Left showing the distribution of staff hours assigned to each project, right showing the project network with staff nodes linked if they were assigned to the same project.
8. Case Study 3: Deployment

identification and graphic layout organisation proposes, but it was less effective in group-wise comparative analysis as the type of work engaged in the departments were fundamentally different. However group-base analytics would still be useful for department managers for the longitudinal review.

8.5. What’s Next

This case study highlighted many real world adaptation issues. The group analytics I developed have assumed the fact that the people can be clearly separated into their groups: no shared membership. In fact, as was recorded in the company’s ERP data, people typically collaborate across department borders and the project work needs change from week to week. I chose to use people’s department assignment as the attribute of interest in the main case study analysis, but I am interested to pursue and expand my DSINM to accommodate dynamic group attributes. This will allow my system to support project-based analytics on cohesion and diversion network behaviour that are known to be indicative of a creativity shift (Waber 2013).

While my research focused on uncovering people interaction behaviours, my collaborators at the host company worked on extracting space usage patterns from the same dataset. They began their exploration with the BLE system, but when they hit a data collection hurdle because at that time the Apple’s iOS did not support background data logging for Bluetooth, they shifted their creative and technical minds to work on space usage data analytics based on my ZigBee data. Below is an example of their work (Figure 39 reprinted with permission), demonstrating the successful knowledge transfer of people tracking analytics through our collaboration. Not long after the conclusion of our productive collaboration, an office space developer that specialised in flexible workspaces acquired the host company. One of my project partners now leads the company’s research and development team with an interest in data-driven space utilisation research.

Office spaces have shifted from individual cell-based configuration towards a flexible open-plan with mixed-use zoning configuration. Driven by commercial incentives (Haynes 2008), and supported by research suggesting that an increase in informal interactions between employees has made a positive contribution to productivity (Pentland 2014; Waber 2013; Boutellier et al. 2008), this trend is sure to continue. Extensive research supports the proposition that the geometrical layout influences human behaviour and communication patterns between individuals (Boutellier et al. 2008).

Further work to incorporate ERP data with the IPMS data will enable managers to use the spatial usage and interaction insights to better match the organisation structure.
8. Case Study 3: Deployment

Figure 38.: Extracting subnetworks from the top three projects (coloured) and comparing their network properties to the overall network (black).

Figure 39.: Space usage analytics based on the ZigBee tracking data developed by my collaborators. (Copyright Case Design Inc., reprinted with permission)
and task dependencies to optimal organisational performance.

This case study also demonstrated the positive effect of people tracking insight to stimulate office culture and improve social cohesion. This bottom-up, grassroots approach was also a simple and effective way to attract and maintain participation. One important aspect of this was its need for close observation of the participants in their context to deliver quick responses. With more case studies, I hope to further develop generalisable strategies that deliver insights targeted for individuals.

The importance of scale will be an important issue when deploying this setup to a larger organisation. Apart from the technical system limitations, the practicality of managing thousands of participants compared to the fifty or so that I had in my case studies will reveal new challenges. For example, how to keep everyone equally informed and coax them into a better state of understanding and participation. Large organisations have more complex management structures and physical setups. Managing data and insight access while balancing privacy issues will be a critical topic to resolve.

8.6. Summary

The case study demonstrated the potential of a people tracking system to provide insights for daily operation in a professional industry context. Complex adaptation issues were resolved with a user-centric approach. Ongoing insights provided participants with a positive incentive to continue participating. Involving the organisation throughout the whole process and knowledge sharing helped me gain trust and gave people a sense of ownership in the study. This model is a starting point for planning long-term people tracking data collection for workplace productivity research.


9. Discussion

Following on from Chapters 6 to 8 that focused on individual case studies, in this chapter I will discuss several overarching topics in this research.

At the start of my candidature I set out to investigate what makes people work better together. Very soon, I discovered how big this quest was. What context should I focus on? How should I judge what is “better”? I looked for a lead which allowed me to dive deeper, but simultaneously remembering to be conscious of linking my work and discoveries back to the real world.

One revelation that struck me very early on was the individuality of each person. We all have our own skill sets that are built up through our unique life experiences; we all have our habits and methods for conducting our work and communicating with others. I realised that instead of the generalist approach of giving people a set of rules and guidelines, an alternative approach is to provide people with information so that they can make their own decisions.

This realisation of individuality gave rise to my user-centric approach that is the centre of this research. Through my real world case studies, I became appreciative of the importance of context in my research explorations; context is also the carrier that transfers the knowledge of my research to my users. The research ethical code of conduct was core to my user-centric approach. I have achieved great outcomes by taking a proactive approach and using ethical principles as a guide to encourage better engagement with my participants. Based on the experience of engaging my participants in my case studies I have summarised the strategies that one should employ to ensure the success of active people tracking in workplaces (Figure 40).

In the next section I will explain how I envisioned the host organisation managers and the study participants as users and proactively engaged them in my holistic people centric approach. Section 9.2 expands on the need to identify my users and the context that they operated in, and how that framed the analytic development process which allowed me to fine-tune the behavioural model to reveal insights from the data. I also used my data exploration process as an inspiration to design analytical insight reports for my users. Section 9.3 puts the spotlight on ethics, especially tackling the difficult but
Figure 40.: Trialled and tested strategies to establish active people tracking in workplaces.
9. Discussion

critical issue of how to ensure voluntary participation with full consent in a workplace environment where there are unequal power relationships.

9.1. A Holistic People-Centric Approach

My research investigated the application of indoor people tracking to reveal actionable insights in workplace environments. Through real world case study based investigations, I am making the claim that adopting a holistic people-centric approach is essential for people tracking technologies to be successfully integrated into the workplace practice. In this context, a successful integration is evaluated by its viability, ethics and continuity. For an organisation that wishes to incorporate people tracking applications into its practice, it is critical that the people being tracked are at the forefront and plays a centre role throughout the whole process, from the initialisation of the study through to development of the analytics and deployment into the organisation’s workforce (see Spotlight on a holistic people-centric approach).

9.1.1. Challenges

People are understandably wary of technologies that they are unfamiliar with. For a tracking system that is based on wireless technology, it is hard to visualise its limits (also see Section 9.3.1). I have had many queries from my participants about whether the system will track them if they go to the rest room. People are also very sensitive about their data, such as what is being captured and how will it be used. I have been fortunate in my case studies to have organisations and participants that are welcoming from the outset (Section 8.2.1). I am very conscious that data is power; participants hand over their data along with their trust and for that reason, it should never be abused.

In the pilot Discovery case study, I was a tutor in charge of several of the student participants (Section 6.3.1). Before the commencement of the study, I identified the possible risk of the influence the generated data on how the student participants were to be assessed for their academic performance in the workshop they were enrolled in. At that early stage of my research, I was uncertain of how participants would respond to the case study. I was very cautious to minimise the tasks required by the participants and the risk to the participants. I chose to identify the data only by the tag serial number and focused on live data analysis on spatial usage, so that less emphasis was placed on individual’s behaviours. I deliberately waited until after the student assessments were finalised before I began to work on the analysis of individual behaviours. While I was working on developing the analysis, I found that many of the uncovered insights would
9. Discussion

<table>
<thead>
<tr>
<th>Spotlight on a holistic people-centric approach: Check list</th>
</tr>
</thead>
</table>

Use the recommendations in this check list to design a holistic-people centric tracking system. The aim of these recommendations is to improve the general reception of a people tracking project, encourage more sign-ups, better participant retention, and ultimately improve the data quality and overall success of the project.

**Planning**

- ✔ Select an appropriate tracking technology based on the context and data needs.
- ✔ Examine the possible risk of the tracking system and data analytics on the targeted people, reduce unnecessary risk.
- ✔ Design mechanism for participants to opt-in to parts of the tracking exercise and simple temporary opt-out methods.
- ✔ Derive strategies to encourage participation including developing targeted analytical reports for the participants as incentives.

**Introduction**

- ✔ Give clear introduction to all possible participants and stakeholders regarding the tracking system and how it will function.
- ✔ Be transparent regarding to the aim and possible risks.
- ✔ Respond to questions and concerns.

**Ongoing**

- ✔ Schedule regular interactions with participants to report on findings and collect feedback.
- ✔ Arrange platforms for people to ask questions, voice concerns and provide suggestions.
- ✔ Respond to feedback in a timely manner.
- ✔ Observe the system in operation.
- ✔ Identify impromptu opportunities for further participant engagement and means for participants to partake.

**Analytics**
9. Discussion

- Use contextual knowledge (such as ERP, space allocation, event calendar and unscheduled activities) to assist the interpretation of the data.
- Encourage participants to submit analytics requests.
- Present findings to participants for feedback.
9. Discussion

have been useful during the workshop (Section 6.4). For example, the timeline plot (Figure 3) of all of the team members would have been handy to identify who were away so that absentees could be informed of the decisions made during their absence. In the next case study (Exploration, Section 8.2.3), I introduced the strategy of displaying live data visualisations during the data collection period. This way the participants could see their data and be certain of what had been captured; also seeing it together with everyone else’s data gave them a sense of participation. This built their trust in the study, cultivated their interest and positively contributed to participant retention rate.

9.1.2. Benefits

Once I had gained the participants’ trust, they genuinely wanted to be helpful and many went out of their way to help the study succeed (Section 7.4). Frequently I had people approaching me asking for more details on the project. They showed a clear interest and freely offered their opinions on the technical and commercial applications of people tracking. On-site participatory observation was one way for me to capture these contributions. Another more structured platform for feedback was regular focus discussion meetings. I used focus discussion meetings in Deployment to share project progress with a group of interested participants and gather their feedback (Section 8.2.2). During these sessions, I received many suggestions on the experimental setup and analytical methods that were very beneficial to my study.

The sense of contribution was also a positive motivator for participation. During the times when I had live data visualisations displayed on the overhead projectors, I had many people approach me to show them where they were in the visuals, and once satisfied they would go and pull their friends to the front of the screen to show them. From the questionnaire feedback I knew that participants also utilised the online visualisations to check on their own data, viewing them many times throughout the data collection period.

The sense of ownership is very powerful. Fostering this is essential to achieving the ultimate goal of successful practice integration. Having a strong sense of ownership, participants will take it upon themselves to maintain the system and self regulate tag carrying. For example in Discovery (Section 6.3.1), participants were students working on an application based on the tracking data. As their work depended on the system output, it was in their best interest to maintain the system’s operations. They were also active participants, continuously wearing the tags throughout the data collection period as well as participating in extra tasks such as system calibration. In Deployment, I gave several staff from the organisation access to the system status and low-level controls,
enabling them to monitor the tags and view the overall system status. They were able to keep the system running while I was off-site. The staff in charge of maintaining the participation rate took the initiative to send regular reminders to people who left tags behind. As those reminders came from people within the organisation, it was less hostile and people were more willing to comply (Section 8.3.3).

9.2. An Analytic Grounded in Context: The insider insight

Through working on the real world case studies, it became apparent that data collected from people tracked must be interpreted with the context in mind. Numerical results are meaningless without grounding it in the reality that they were collected from. In my attempt to make generalised findings on human behaviour across the three different case studies, I was constantly reminded of the importance of contextual knowledge, which I gained by immersing myself in the activities alongside my participants. The tracking system is a window into otherwise invisible entanglements between people and the space. It offers insights to enrich one’s understanding of their own behaviour. Its greatest potential is in engaging people in reflective discussions and offers a basis for learning from experience (Sections 8.3.3 and Spotlight on user feedback). It should not be treated as a remote system that sends out automated warning messages to management, and is definitely not to be used as the sole evidence for decision making.

The standard practice of SNA research has been to demonstrate its application with a few well-known datasets or data sources, and its focus is quite generalised. The selection and interpretation of advanced SNA methods for context specific datasets such as the tracking data was a challenge for me. I sought to gain expertise in SNA to help me tackle my case study tracking data. I quickly realised it was not possible to simply throw the data at any SNA method and expect comprehensive findings. Looking solely on the quantities data, I was not able to determine whether discrepancies in the results were from limitations in the data collection process, the behaviour model or abnormal events. I had to draw on my on-site experience to pull up additional scenario references to iteratively evaluate and refine the analysis for the particular context (Sections 7.3.1 and 7.3.2).

My typical data analysis process was as follows: First I selected a data sample that contained an event of interest, such as group meeting. I then constructed a simple network model that revealed group behaviour and applied it to the data. This network was then processed using a low-level network analysis technique (such as degree centrality) and visualisation to verify the behaviour model was appropriate, if not then the
behaviour model was refined. More advanced network analysis was then applied; the data visualisation was updated if required to highlight the analysis findings. Once I was satisfied with the analysis pipeline from modelling to visualisation for one sample, I evaluated this with another known data sample. This process was repeated until I was confident with each component of the analysis pipeline. I then expanded my sample to apply the process to the rest of the dataset. This highlighted the importance of contextual knowledge in the data analysis and evaluation process.

A similar process allowed the users to bring out their own experience to interpret complex data processing methods. The users were first presented with a sample data overview in a layout appropriate to their professional industry. This helped to build a conceptual understanding of the behaviour captured in the data. Next, simple data manipulations were presented to introduce the users to the concept of network modelling and analysis. At this stage, multiple examples were used to reinforce knowledge before more advanced analysis were presented using the same data examples. Users were then encouraged to explore the process by scrolling through the dynamic data visualisations of the complete dataset and flipping between different data analysis. This allowed people to familiarise themselves with the data context, and to apply their contextual knowledge to draw insights from the analysis. I used this context-centric analytic approach to structure the way in which I presented the data to my participants in the system introduction, data finding presentations and online web-based data reporting (Sections 7.2.3 and 8.2.3).

9.3. Spotlight on Ethics

There is a misconception in academia that the ethics application process is paperwork that hinders the research process. When I first started developing my research data collection methods, I talked with other researchers about their experiences on human research. I heard lots of “you’d never get that through the [ethic] board” and “[I] looked for ways to strip back the experiment so that it was ‘low risk’”. There was a general negative attitude regarding the ethics application process; people considered the university ethics board as a risk avoidance structure put in place by the university. There were also views that the potential participants would not sign up to the study if they were told too much.

A better approach to these risk avoidance views is being proactive. The ethics application process informs the design of the experiment. This frames the project parameter discussions with the host organisations from the outset (Sections 8.2 and 8.3.1). There is a vast range of data collection methods available to the researcher, and each carries
pros and cons on the labour needed to collect and code the data, but importantly it also has impact on the participants which must be factored into the planning. Efficiently selecting data collection methods that are not a burden, but rather are pleasant for the participants will encourage more people to remain involved in the study.

Providing immediate feedback to the participants has the dual benefit of being an effective means to retain participation and to guarantee informed consent (Section 8.2.3). This could be done at multiple points during the data collection process. At the participant sign up stage, potential participants could be shown analysis of the test data, or even better live data from the system in operation. This allows people to be better informed on how their data will be used. Once the participant registration is complete, a notification email should be sent out to all participants with instructions on how to access their data and details of the analysis. This gives participants access to their data to verify their consent. At appropriate intervals, emails can be sent with a report on the latest insights revealed by the data, allowing participants to be engaged and communicate any queries they may have. At the conclusion of the data collection period, a report of the overall exercise can be delivered with the participant experience questionnaire. Participants were more likely to respond and give detailed responses to the questionnaires that were presented alongside the outcomes of the study.

9.3.1. Handling Consent and Data Collection in Shared Spaces

With the abundant availability of personal data people released into the world, many researchers also justify that this data is free to take. A recent controversy highlighted this moral dilemma (ABC News 2016). Although in this incident the organisation’s action might be legally valid, this can be seen as a breach of moral ethics of care. It is unfortunate that the organisation did not see this as an opportunity for community engagement. A better approach would have been to inform all the people involved in the study with a description of the data that was to be collected, a timeline of when the data collection will be taking place, and an explanation of the use of the data. During the data collection period the organisation should display public notices to inform the public that the data collection is taking place. There should also be a channel for people to request more information and to refuse consent.

In two of my case studies (Exploration and Deployment), the observed spaces were shared between the case study participants and people outside of the studies. Before the data collection equipment was in space, a plain language statement was emailed to all of the space’s occupants, informing people of the nature and duration of the data collection, and the risk to privacy. With Exploration, the building was open to the public, so public
9. Discussion

notices were posted at the entrances and on notice boards. In both of the case studies, I had people approach to me to ask for more information on their privacy, most queries were about privacy in the restroom and whether they could be tracked at home. For most people, the range of wireless indoor tracking sensors was harder to grasp than the familiar line-of-sight range of security cameras. My explanation was that the wireless sensors I used have a limited range of about ten metres, so there was no risk that they will be monitored at home; although there were no beacons in the restrooms, tags might get picked up by nearby beacons, so I assured people that people’s behaviour outside the work area will not be part of the study. I recommended people to leave the tags at their desk any time that they do not want to be tracked. People were satisfied with these explanations and happy to sign up to the study. Throughout all of the case studies I received no complaints and no withdrawals on privacy grounds. (I built a data filter to remove the idle tags, although I have to keep in mind when interpreting the analysis results that some of the discarded data might be false positives from people being very still.)

9.3.2. Tracking in the Workplace

More and more corporate organisations are interested in indoor tracking in their workplaces. Employers may implement workplace surveillance procedures for reasons such as security and productivity monitoring (Moussa 2015; Chang, Liu, and Lin 2015). Privacy practice varies across the globe and industries. In Australia, there are laws that protect employee’s privacy in the workplace (such as The Government of Victoria, Australia 2006). In summary, with prior information and assumed consent, employers are able to install surveillance devices (such as camera or tracking devices) to monitor their employees while they are at their place of work during work hours (Fair Work Ombudsman 2014).

Although the legislation states the bare minimal that an employer is required to do, my work demonstrated that going beyond this and engaging the employee with the process fosters positive participant relationships and produces better overall outcomes. Rather than a bleak picture of ethics of surveillance in workplaces painted by some academics (Introna 2002), my work offers a positive outlook to achieving a non-zero-sum game involving all stakeholders. In my Deployment case study, I gained valuable suggestions and publicity by being open about my methods and motivations, and sharing real time data visualisations with the participants (Section 8.2). During the data collection period, people approached me to ask about the data, find out more about the research, suggest behaviours to analyse, and offer their feedback on their experiences in the study. People
9. Discussion

requested to be included in the study at the recommendations of their colleagues.

We must also acknowledge that there will always be a conflict of interest between the involving parties even with the best intentions. Marx (1998) argued that “in the age of new information technology the matters [of ethics of surveillance] is so complex and varied we are better served by an imperfect compass” and authored a list of questions to guide us in decision making. On reflection of my own work, *knowledge is power* has been an underlining thought influencing my design decisions through out this research. When in doubt, I have taken to trust my users by giving them the knowledge and power to control and make changes for themselves. This was part of my strategy to build trust with my participants as well as forging trust between the power relations amongst the different group of participants. On one hand, I am fortunate to report that I have not had one incident of breach of trust or abusive of power with my three case studies, on the other I am deeply aware that my case study scenarios are not fully representative of the greater workplace. It is beyond the scope of this thesis to explore in depth how I can stop the system to ‘do no evil’ once it leaves my hands, but it is a topic that I am passionate to explore and be active in shaping in the future.

9.4. Summary

In this chapter, I present my reflection on a few of the overarching issues that were central to my research.

A people-centric approach is the focus of this research. I regard the participants of my research case studies as my users and catered to their needs. I gained participants’ trust by maintaining transparency and being attentive to their expectations. I actively cultivated participant interest and their sense of ownership in the process. A people-centric approach was essential to the success of my case studies, and is recommended for any organisation that wishes to introduce people tracking to their existing practice.

I framed my research within the specific context of each of the case studies. This framing specified my users and I used their point of view to determine what insights were relevant to them. I looked to my users’ needs as reference points for all of the design decisions in order to adapt my research to each of the case studies. This ensured the representative data was captured during data collection, the relevant behaviours were modelled for analysis, the activity specific analytics were used to uncover insights, and the profession appropriated reporting style were used to present findings to my users.

My work demonstrated the benefits of a holistic view to handling ethics. I identified the risks of people tracking in the workplace. By being transparent to my participants,
9. Discussion

I ensured that they made an informed decision on participation. I actively engaged the host organisation and participants in every stage of the case study. I responded to their needs and used the in-build amendment flexibility to adapt the study to harness new opportunities. This transparent knowledge sharing model builds trust, trust lays the foundation for rapport, and rapport leads to better participation and data quality.
10. Conclusion

This research demonstrated the adaptation of a user-centric approach to deploy a wearable sensor network to provide targeted insights to members in workplaces.

Data provides valuable insights for better decision-making, and studies have shown certain aspects of an organisation and project management processes can benefit from monitoring physical interactions within the workplace. Behavioural monitoring is often seen as intrusive and for this reason people are reluctant to participate. This is more problematic in workplaces, as employees are wary of the intrusion on their privacy and how their performance may be misinterpreted by the data, as well as the fact that legislation is often in favour of the employer.

Through a series of real world case studies, I investigated strategies to incorporate people tracking into organisational management practices in an ethical and sustainable manner. More importantly, I tackled the often-overlooked stage of adapting a prototype setup into the day-to-day practice with ongoing participation, sustained data quality and system operation.

Utilising the participatory action research (PAR) methodology, I iteratively developed a user-centric approach and successfully established active people tracking in three collaborative work environments. My approach identified the tracked individuals alongside other stakeholders as the user of the indoor people monitoring system (IPMS) and the needs of the user were considered in all stages of the system design and deployment process. This active user engagement facilitated technical and contextual knowledge transfer between I, the system consultant, and the organisation stakeholders.

In the process of this research, I developed an IPMS system that delivers insights into teamwork dynamics revealed by tracking the social network interactions that occur within collaborative work environments. The working prototype is capable of simultaneously monitoring the progress of multiple cohabiting project teams. The flexible Dynamic Social Interaction Network Model which I developed constructs customised social networks to extract interactions of interest from the tracked data to provide context specific insights. The analytics generates visually rich reports layered with contextual cues enabling quick cognition by the intended viewers. The targeted user spans all levels
10. Conclusion

of the organisation from project collaborators to support personnel and upper management. This setup empowers everyone with a data-supported reflective learning process.

The case studies demonstrated the importance of transparency and knowledge sharing throughout all stages and aspects of the process. This was essential for building trust and rapport with the tracking participants, and had the added benefit of increasing participation. In contrast to other top-down people analytics practices, my approach engages individuals with targeted insights. This rewards ongoing engagement, and in turn maintains participation. Fostering grassroots ownership of the process supports an integration that is aimed to be sustainable and self-sufficient. This is critical for a successful system handover.

In summary, the original contribution of my research is two-fold. Firstly, I demonstrated the technical capability of a people tracking system and analytics to provide real time insights to workspace design, project management and human resources management applications. Secondly, as demonstrated in the Deployment case study, I have proven that a user-centric approach is critical for the successful integration and adaptation of people tracking systems and analytics into real world workplace practices.
A. Published papers

A.1. A multimodal toolkit for thermal performance feedback in conceptual design modelling


Abstract

This paper presents a multimodal toolkit for rapid performance-driven facade design that includes both virtual and physical performance feedback. The toolkit has been user tested in the SmartGeometry 2013 event by the Thermal Reticulations workshop cluster. Although the workshop participants were predominately digital design focused, the authors observed several distinct approaches to the tool selection and workflow involving both physical and virtual simulations, with a favoring to tools that produce fast visual outcomes. The approaches to tool selection are presented here as case studies with their workflow mapped for discussion. We conclude that access to a diverse range of simulation tools for design evaluation is advantageous to the creativity of the design process.
A multimodal toolkit for thermal performance feedback in conceptual design modelling

Mani Williams, Jane Burry, Flora Salim, Stig Anton Nielsen, Alexander Peña de Leon, Kamil Sharaidin, and Mark Burry

Spatial Information Architecture Laboratory, RMIT University, Australia, Department of Architecture, Chalmers University of Technology, Sweden

Abstract. This paper presents a multimodal toolkit for rapid performance-driven façade design that includes both virtual and physical performance feedback. The toolkit has been user tested in the SmartGeometry 2013 event by the Thermal Reticulations workshop cluster. Although the workshop participants were predominately digital design focused, the authors observed several distinct approaches to the tool selection and workflow involving both physical and virtual simulations, with a favoring to tools that produce fast visual outcomes. The approaches to tool selection are presented here as case studies with their workflow mapped for discussion. We conclude that access to a diverse range of simulation tools for design evaluation is advantageous to the creativity of the design process.

Keywords. Tools development, design process, performance-based design, simulation, sensors.

Introduction

The ubiquity of computing and digital technologies has seen the progression of the ways they are used for design, from being a mere drafting aid to something closer to the analogy of a Swiss-army knife tool for generating, prototyping, inspecting, and evaluating design ideas in digital and/or physical representations. Designers such as ShoP Architects now model every detail of the design in a virtual environment in order to extract building information, optimize and simulate building performance. Designing for volatile environments poses some uncertainties, which can potentially widen the margin of error in the performance predictions for buildings in design. Designers increasingly seek to understand the performance of their design through garnering feedback from physical prototyping and analogue simulation of the complex physical environment (Moya et al., 2013). Sensors are tools for designers to digitally infiltrate the physical space. When used in physical simulation, sensors quantify environmental information of the design context and its performance. We propose to extend the current digital design workflow to include physical simulation into a multimodal performance feedback toolkit. The aim is to combine virtual and physical simulations to give designers a more comprehensive understanding of their design’s performance. It is a positive contribution to the design development workflow.

Thermal Reticulations (TR) is a research project that aims to develop tools and platforms to assist designers to better understand the thermal performance of façade design directions in early design. Precedence exists of thermal testing setups in larger scale and of longer simulation durations (Melcher and Karmazínová, 2012); the
novelty of the TR project is our focus on rapid performance feedback from the combination of virtual and physical simulations.

Here we assembled a system of workflow (Figure 1) to model and simulate heat transfer across and through façades. This system is a combination of virtual analyses using open access software as well as physical testing and comparison of prototypes for understanding thermal behaviors of the façades. Feedback included real time visualization, interpreted visualization and collection of numerical data. TR was one of the workshop clusters in the SmartGeometry 2013 event (SG2013). Designers from academia and industry participated in the four day intensive hands-on workshop to explore thermal performance in façade design. The toolkit enabled the designers to produce multiple design iterations and conduct thermal simulations using multiple approaches.

We observed several distinct approaches to the tool selection. For example there were designers that began with digital modeling and virtual simulation and then progressed to physical prototyping and verification, whereas others approached the process in reverse by conducting physical prototyping and simulation first. In this paper we will present a selection of these approaches and analyze designers’ selection criteria for their choices of tool from the provided toolkit. The opportunities and limitations of the tools are also discussed. We conclude that access to a diverse range of simulation tools for design evaluation is advantageous to the creativity of the design process.

Figure 1 A diagram of available tools within the toolkit and possible workflow paths

Toolkit content

To support a comprehensive understanding of the thermal performance of a prototype, the TR toolkit contained a selection of tools ranging from digital simulation software,
physical sensory devices, to support tools such as data analysis and design-fabrication packages. (Figure 11)

With the toolkit at our disposal, there are multiple workflow paths that a designer can take, beginning with either virtual simulation (Figure 2) or physical simulation (Figure 3).

Figure 2 Example of a virtual simulation workflow (Urquiza, 2013)

Figure 3 Sample physical simulation results (Vergauwen, 2013)
In the next section we present several case studies from the recent SG2013 workshop to demonstrate the TR toolkit in action.

**Background**

SmartGeometry is an annual week-long event, including a four-day workshop and two-day symposium [1]. TR was selected as one of the ten workshop clusters, delivered by the authors to a group of thirteen participants (to be referred as “users” in this paper). The toolkit was developed by the authors to be used during the workshop.

Prior to the workshop, the users received instructions for the toolkit including how to access its virtual simulation components. The users were also encouraged to prepare a model to be brought to the workshop. A short demonstration of the toolkit components was provided at the beginning of the workshop. The users were able to select the simulation workflow to suit their individual design intent. The outcomes of the four-day workshop were presented to the SG2013 attendees during the SG2013 Symposium event both as an exhibition as well as a verbal presentation. A selection of the façade designs is presented in Figure 10.

The case study workflows were deduced from users' design documentations and authors' direct observations.

**Case study one: Virtual-physical-virtual-physical**

![Figure 4 A diagram demonstrating the virtual-physical-virtual-physical workflow](image)

The workflow of this case study is illustrated in Figure 4. The bold arrows indicate the initial design iteration path; the grey arrow indicates where the simulation results feed back into the design process; the thinner arrows correspond to the later design iterations, indicating divergences in the design approach and/or inclusions of additional tools.

In this case the user began with design and simulation in the virtual spectrum before fabricating a physical prototype for physical simulation. The testing results from the two simulations informed the concept for the second design iteration; the physical simulation result was also used to update the boundary conditions for the virtual simulation. Once the user was satisfied with the virtual simulation results of the updated design, it was fabricated and the focus was turned to develop a suite of physical simulation tools to verify the observations from the virtual simulation.

This user repeated the virtual-physical simulation workflow for both design iterations. The virtual simulation section was identical; in the second iteration the physical simulation was expanded with additional testing tools such as thermal sensitive paint, an external digital thermal sensor and embedded thermal sensors to
collect data on different aspects of the design and to compare it with the virtual simulation results. We suspect the set-up requirement of the individual tools influenced the tool selection decisions. With virtual simulation, each software simulator is produced by a different developer so the input parameters are not fully compatible. In the case of physical simulation the authors designed the simulation set up with compatibility as an important design feature, for example the two simulation boxes have the identical façade fixture specifications.

**Case studies set two: Virtual-physical-physical**

This set of case studies (Figure 5) has the workflows similar to the virtual-physical-virtual-physical where the users began their concept development with digital modeling and virtual simulation. The departure from the previous case study is that in this case the users moved away from virtual simulations quickly. They were more interested in producing multiple iterations of physical prototypes for physical simulations. Only the "skeleton" of the design was simulated virtually, multiple iterations of the concept were realized as physical prototypes and progressed through physical simulation only. This set of case studies demonstrated a preference for conducting in-depth simulation with physical tools over virtual tools.

**Case Study three: Physical-virtual-physical-virtual**

This user began the workflow (Figure 6) in the physical spectrum before moving to virtual simulation. The duo physical-virtual simulation process informed a revised concept for the second simulation iteration. Although the revised design was modeled
with digital tools, the user still followed the physical-virtual workflow from the first iteration, with the addition of thermal sensitive paint into the physical testing toolset. This case is the reversal of the first case study virtual-physical-virtual-physical, and similar to the first case, this user preferred to experiment with physical simulation workflow and kept the virtual simulation workflow identical.

**Case Studies set four: (Digital modeling only)-physical-physical-virtual**

In this set of case studies the users developed the initial concept with digital modeling tools but used physical simulation tools to inform the subsequent development iterations. Virtual simulation was conducted after satisfactory simulation results were achieved through the use of physical simulation tools. (Figure 7)

These users also showed an early preference towards physical simulation over virtual simulation. Virtual simulation was used to verifying the physical simulation results. The diagram on the right in Figure 7 right demonstrates an interest to experiment with additional virtual simulation tools.

**Other cases**

There were users that selected to conduct only one spectrum of the simulations. Multiple design iterations were still achieved. (Figure 8) Factors such as unplanned delays in fabrication caused some users to miss out on some of the simulation opportunities; there were also users that made a conscious decision to concentrate on one spectrum of the simulation only.
Analysis

From the presented case studies, it is clear that the workflow undertaken by the users of the toolbox varies. In the SG2013 setting, the users were highly encouraged to use a wide range of the tools in the toolkit. Considering the focus of SmartGeometry on computer aided design (Peters and Peters, 2013), it is not surprising that many users began their workflow with the digital modeling tools. Although the recommended virtual simulation workflow was presented before the physical simulation tools and workflow, this did not deter users from selecting physical simulation workflow for their initial design simulation. The intensive mode meant that tools that produce quick visual results were favored, for example the selection of thermal imaging camera over the digital sensor network. Users were also interested in the time variant of the simulation. Videos of the time-lapse of the thermal imaging captures and animated sensor network results were well received.

Many of the tools in the toolkit were new to the users, especially the selection of virtual simulation tools. Simulation set-up was an influential factor of tool selection; some users expressed frustration with the strict input requirements of some of the virtual simulation tools. Difficulties such as a model's failure to mesh (required for the simulation software Elmer) meant that some of the digital models had to be simplified or remodeled before being put through the simulation workflow. In comparison, users with prior fabrication experience could make physical prototypes close to their original intent. The two simulation boxes had the identical prototype fixture specifications and were designed such that the prototypes could be smoothly installed and removed. The testing equipments were also relatively easy to apply. A prototype could quickly switch between different physical simulation set-ups. This ease of use meant that we observed a more varied physical simulation workflow path when inspecting the workflow patterns.

A question raised during the development of the TR workshop was how to compare the simulation results between physical and virtual simulation workflows. The rigorous interpretation of the numerical data from both virtual and physical processes would require time and appropriate statistical analysis, which was not available during the workshop. The physical simulation tools are sensitive to the uncontrolled room conditions, unlike virtual simulations where a constant boundary condition can be set. Small changes in starting conditions could affect the fluctuations of the logged sensor data. Therefore, it is likely that the actual figures will need to be manipulated to provide direct comparison between the tests of different façades with any veracity. This also means that the physical simulation workflow can illuminate the performance issues caused by the combined effect of multiple design and environmental parameters. The virtual simulation tools are deterministic and reproducible, but to receive results that are appropriate for quick design decision-making, compromises have to be made in terms of model and environment complexity.

It was apparent that the users were less interested in comparing the results for contradictions, but welcomed the additional design understanding from using a variety of simulation tools. As shown in Figure 9 more than half of the users incorporated both physical and virtual simulation tools into their workflow. Under the workshop setting, users observed and learned from each other's simulation results, adopted certain design features or tried out different simulation tools. Offering tools that have minimal comparable outcomes turned out to be of a greater advantage than we had anticipated. We have received positive user feedback on the enriching effect of offering a broad selection of tools for design development. Users reported that the
use of the toolkit enabled rapid performance-based design iterations; other users noted that the experience helped to build design intuition and sharpened design thinking.

Future work

It would be beneficial to incorporate other forms of environmental sensors into the physical simulation set up, such as humidity, lighting and airflow to name a few.

We have observed from the simulation results that the thermal gain reached the simulation boundaries within minutes. We are investigating scaling-up the experiments to room-size so that the simulation results are more relevant as a façade testing toolkit. This is easily done in virtual simulation, and in physical simulation we can remove the need for the simulation box and conduct the data measurement on location.

Summary

In this paper we presented a multimodal toolkit for thermal performance feedback design.

We have demonstrated the successful extension of design development workflow with a physical simulation component. Through the presented case studies we have shown a wide range of workflow and design approaches undertaken by users in an intensive workshop setting. The TR toolkit combines virtual and physical simulations into a multimodal toolkit to give designers a more comprehensive and intuitive understanding of performance-based design and thus is a positive contribution to the design development workflow.

Acknowledgements

The authors would like to thank the following participants and support for their contribution to the Thermal Reticulations project:

- Consultants: Ian Ridley (RMIT), Philip Biddulph(UCL),
- Support: Shuying Zhou and Chen CanHui

Sponsors: RMIT University, SmartGeometry, Bentley Systems
References


<table>
<thead>
<tr>
<th>Name</th>
<th>Application</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design</td>
<td>Digital modeling software</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rhino3D - Grasshopper (Rhino plugin)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Digital Project</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Generic Components</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Processing</td>
<td></td>
</tr>
<tr>
<td>Segmentation tools</td>
<td>Prepare digital models for simulation</td>
<td>Design tools can also perform segmentation</td>
</tr>
<tr>
<td>Salome</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MeshLab</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Virtual simulation tools</td>
<td>2D (sectional) thermal simulation</td>
<td></td>
</tr>
<tr>
<td>Agros2D</td>
<td>Both temperature and humidity, 1D (point) data</td>
<td></td>
</tr>
<tr>
<td>WUFI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elmer</td>
<td>3D thermal simulation of both the model’s material and its environment</td>
<td></td>
</tr>
<tr>
<td>Physical fabrication tools</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hand tools</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laser cutter</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3D printer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical simulation tools</td>
<td>300x300x400 (mm) testing volume</td>
<td>Replicate in virtual testing</td>
</tr>
<tr>
<td>Simulation boxes</td>
<td>2 versions: sensor box and imaging box</td>
<td></td>
</tr>
<tr>
<td>Heat lamp</td>
<td>Heat source, 500W halogen lamp</td>
<td>Replicate in virtual testing</td>
</tr>
<tr>
<td>Thermal imaging camera</td>
<td>Measure surface 2D data</td>
<td></td>
</tr>
<tr>
<td>Infrared thermometer</td>
<td>Measure surface point data to calibrate the virtual simulation boundary conditions with the physical simulation</td>
<td>Handheld device</td>
</tr>
<tr>
<td>Analogue thermal sensor</td>
<td>Point data, internal temperature of the prototype</td>
<td></td>
</tr>
<tr>
<td>Digital thermal sensor</td>
<td>Point data of the environment</td>
<td>1-wire DS18B20</td>
</tr>
<tr>
<td>Digital thermal sensor network</td>
<td>3D thermal distribution of within the sensor box</td>
<td>27 DS18B20</td>
</tr>
<tr>
<td>Arduino</td>
<td>Sensor control and data communication to PC</td>
<td></td>
</tr>
<tr>
<td>Data logger</td>
<td>Purpose built API to communicate to the Arduino and log the sensor data into a CSV file format</td>
<td></td>
</tr>
<tr>
<td>Analysis tools</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ParaView</td>
<td>Visualizing simulation data from Elmer and data logger</td>
<td></td>
</tr>
<tr>
<td>Matlab</td>
<td>Visualizing data logger output as 2D and 3D plots</td>
<td></td>
</tr>
</tbody>
</table>

*Figure 11 List of the toolkit contents*


A. Published papers

A.2. Applying social network analysis to design process research, a case study


Abstract

This paper presents a novel approach to analyse design project development demonstrated within a collaborative design case study. We present the limitations of the existing protocol-based design process analysis in analysing real design scenarios. Taking a complete set of regular meeting notes from a design project, the study translated the record of design discussions and decisions into a decision network. We then selected three Social Network Analysis (SNA) methods to apply to the network to analyse different aspects of the project development. Degree, betweenness and clustering focused on three different resolutions of the design process, offered quantitative ways to analyse and visualise the design decisions in both short term as well as over the whole design process.
APPLYING SOCIAL NETWORK ANALYSIS TO DESIGN PROCESS RESEARCH, A CASE STUDY

MANI WILLIAMS,¹ JANE BURRY,² and ASHA RAO³
¹,² Spatial Information Architecture Laboratory
³ School of Mathematical and Geospatial Sciences
RMIT University, Melbourne, Australia
{mani.williams, jane.burry, asha.rao}@rmit.edu.au

Abstract. This paper presents a novel approach to analyse design project development demonstrated within a collaborative design case study. We present the limitations of the existing protocol-based design process analysis in analysing real design scenarios. Taking a complete set of regular meeting notes from a design project, the study translated the record of design discussions and decisions into a decision network. We then selected three Social Network Analysis (SNA) methods to apply to the network to analyse different aspects of the project development. Degree, betweenness and clustering focused on three different resolutions of the design process, offered quantitative ways to analysis and visualise the design decisions in both short term as well as over the whole design process.

Keywords. Social Network Analysis (SNA); data visualisation; tool development.

1. Introduction

The process of design in the built environment progressively becomes a more collective team effort, combining expertise from specialist designers and technical consultants (Spence et al 2001). It is vital that we understand what occurs during these collaborations so we can better support the change in the design practise of today.

Unveiling the cognitive process of collaborative design has been the focus of much scholarship. Protocol analysis, first applied to design processes by Eastman in 1968, was applied to collaborative design in the well-known 1995 Delft Protocol Workshop (Cross et al 1996). Classification of the protocol into a series of “design moves” and design reasoning “links” quantifies the design process into a format for static analysis and visualisation, a method coined as Linkography by Goldschmidt in 1990. Kvan and Gao (2006)
applied Linkography to protocols from collaboration in three different design settings.

A major shortcoming of the standard Protocol Analysis is that it is inaccessible for a real world design scenario. A comprehensive Protocol Analysis requires extensive observation including a complete transcript of interaction between members and detailed observation notes, making it difficult to apply to design processes that are more than a few hours long. For design scenarios of long durations researchers need an alternative data source and analysis method that is practical.

One common practice in collaborative projects is the recording of minutes during team meetings. If the team meets regularly and minutes are recorded consistently, then it is fair to assume a complete set of meeting minutes contains the essential design decisions made throughout the project.

We propose a novel approach to examining the design process by extending the standard Linkography analysis to include parameters from Social Network Analysis (SNA). We will demonstrate this with a case study. We suggest that the selection of SNA methods and visualizations can give insights into different aspects of the collaborative activity such as idea convergence (Figure 3), critical discussion identification (Figure 6) and topic clustering (Figure 7).

In this paper we will first present the case study. The results from a careful selection of SNA methods will then be discussed in the context of design development. We will also speculate on ways to integrate SNA methods into the design process to inform design decision-making.

2. Case Study

A multi-disciplinary team was assembled to tackle a trans-disciplinary design problem: to prepare a design workshop that investigates an environmental phenomenon through digital and physical simulation. The set of meeting minutes used in the study documented the project discussions and decisions from the four months of weekly team meetings, covering the project development and delivery stage. The meeting items were reviewed for associations across consecutive meetings; each association was identified as a link and is stored into a database for further analysis. There were 385 links extracted from the 206 items across the 15 meetings. The Goldschmidt Linkography representation is presented in Figure 1. This set of links had the link index of 1.87.
As the items were naturally grouped into meetings and links were only considered across consecutive meetings, Figure 2 represented the items in 2D and mapped the link information accordingly.

If we observed only the Linkograph, it was easy to draw the conclusion that the project had two phases that divided at Meeting 7 or 8. Looking at the 2D network representation it became clear that this appearance was the result of having fewer items discussed during these two meetings. There were no Linkography “chucks” observed from our case study; this could be explained that all the links were only recorded across meetings thus not possible to observe large sections with little overlapping. This nature of the links meant it was also not possible to observe “sawtooth track”. “Webs” could be observed between meeting 1-2, and 14-15, but from the 2D network we could see that there were also a concentration of links between Meetings 2-3, which was less obvious from the Linkography representation.

From the above comparison we could see the limitations of the Linkography method to analyse the discrete sets of meeting items. For this we proposed to introduce quantitative methods from SNA into the design process research.
3. Application of the SNA measures

SNA is a branch of Network Science, which considers the discrete objects as social entities (nodes) and focuses on the relationship between the objects. In context of this case study we defined the meeting items as nodes and the identified associations of the items across consecutive meetings as the links. We have applied a selection of SNA methods and measures to the meeting item association dataset. These measures covered analysis over multiple scales, from the local node level to the global-network level.

3.1. DEGREES

Degree is the number of links that belong to each node; it is a measure of the local connectivity of the node. For a directional network, the distinction can be made from in-degree (number of direct links that arrive at a node) and out-degree (number of links that are originated from a node). In the context of our study, the degree measure gives indication of how an item is explored between two meetings. To enable the measures from different meetings to be comparable, the definition degree values were normalised by the number of items in the corresponding meetings.

![Figure 3 Normalised in-degree measures](image)

The in-degree measures gave an indication of how well the current meeting item is considered from the discussions in the previous meeting. Observed from Figure 3, it was not surprising that the final meeting (Meeting 15) contained many high in-degree items, as they were summarising discus-
sions that concluded the project. Meeting 2 also contained many high measure items. This was the meeting that the concept of the project was being consolidated, after the group members had a chance to consider the project post the introductory meeting (Meeting 1). This measure also highlighted interesting items in the intermediate meetings. For example the two high measure items in Meeting 9 were discussions on the limitations of the system and setting a deadline for one component of the project to be completed by the next meeting.

Figure 4 Normalised out-degree measures

The out-degree measures gave an indication of the influence of the current meeting item to the discussions in the next meeting. For example the highest measure items from Meeting 1 corresponded to the decision to have three foci in the project (physical, digital and theoretical); the item from Meeting 8 recorded a discussion on the project delivery schedule and plan (What needed to be resolved in the next 5 weeks.). (Figure 4)
The combined un-directional degree measures indicated the importance an item played in the short term, considering both the convergence and divergence of discussions. Presented together in Figure 5, the visualisation demonstrated the dynamic aspect of the project progress for this case study: Meeting 5 was a more balanced set of discussions, compared with Meetings 10 and 11 where less connected issues were discussed alongside more connected ones. When we referred to the notes from the Meetings 10 and 11 we found that the low degree measure items were discussions around alternatives to one aspect of the design, and the higher degree measure items were discussions on the development of the overall project.

3.2. BETWEENNESS

Betweenness of a node is defined as the number of shortest paths that cross the given node (Freeman 1979). This is a global measure indicating how well situated a node is in the network. This measure can be used to identify bottlenecks or gate-keepers in a network. In our study we expected the betweenness measure to reveal critical moments in the project development.
The higher betweenness measures from Meetings 4, 6, 7 and 8 corresponded to the following item discussions (Figure 6):

1. Design criteria (what scenario and materials?), need to give the workshop participants a clear brief (Meeting 4)
2. Prepare the workshop brief and schedule (Meeting 6)
3. Compile a factsheet for the participants (Meeting 7)
4. What needs to be resolved in the next 5 weeks? (Meeting 8)

Item 1 was a major discussion that set the approach of the project development. Item 2 and 3 were task setting discussions that pushed the progress of the project. Item 4 was a major stock-taking discussion where the team focused on the setting of a timeline and priorities to get the project to completion.

3.3. CLUSTERING

In SNA clustering and community detection are the optimisation tasks of grouping similar nodes according to a set of features and criteria. We have selected the Girvan and Newman (2001) link-betweenness algorithm to group the nodes based on the betweenness, or criticalness, of the links. This algorithm looks at the importance of the links in the context of the overall network and groups together nodes that are more densely linked. The link-betweenness algorithm detected 21 groups within the meeting item network (Figure 7).
As an analysis tool for project progress tracking, this algorithm indicated sections of the project or stages of the project that could be potentially delegated to a sub-team. Looking at the examples from our case study: Group 3, contained single item discussions that spanned across Meetings 3 to 5, was the discussion around locating a testing chamber; Group 11 (Meetings 4 to 6) was on participant selection; Group 9 (Meetings 2 to 7) was about communication with project sponsors.

Looking at the diagram as a whole the project could be divided into 4 phases: Phase 1 (Meeting 1-3), Phase 2 (Meeting 4-6), Phase 3 (Meeting 7-13) and Phase 4 (Meeting 14-15). These matched the project's concept exploration, concept development, fabrication, and delivery phases.

4. Discussion and Future work

By only considering the effect from the most recent meeting to the current meeting, this minimised the workload required to produce item association network that enabled analysis on the complete design process. This set-up prepared the system to be extended into an in-process project management tool that aimed to provide the design teams with up-to-date project information, such as presenting issues covered in the project ranked by importance (degree and betweenness), advice on task allocation and team structuring (clustering) and other numerical and graphical information.

The major shortcoming of this meeting by meeting association was that this ignored item associations within a meeting as well as the discussions that "leapfrogged" meetings. The former could be resolved by an additional
link association process with each meeting that looked at only the items with in the current meeting. To accommodate latter required a much more complex process: the numbers of possible links grows exponentially as the project progresses, if all past items are to be considered when producing links for the new item then. For this to be feasible part of the process it must be automated through an ontology based text association system and/or a recommendations based on machine learning system. Once the links are extracted the same analysis can be applied.

Looking at meeting notes is only one approach to analysis project process, we are planning to apply SNA to other the design process observations scenarios, such as tracking the physical interaction in a face-to-face collaboration workshop. It will be an opportunity to apply similar set of measures to a different setting. From this we hope to better understand the generality of the measures as well as investigate patterns in project developments.

Other SNA literature on clustering coefficients, multi-mode network and dynamic networks (comprehensively summarised in the 2011 book edited by Scott and Carrington) are also relevant for the context of design process research. Further work is required to extend these and develop new SNA measures to build a set of analysis tools for the investigation and applications of the design process management research.

In other aspects of architectural design we believe SNA has the potential to be integrated into the adaptable system design and interaction design. SNA offers new approaches for understanding and learning user behaviour as well as calculating recommendations for system responses.

5. Conclusion

This paper is the early stage of research into multi-disciplinary design processes. The aim of this study is twofold. Firstly considering real-world design scenarios, investigating ways to track and analyse the dynamic of the project development; secondly to extend the current design process analysis methodologies with quantitative methods.

The standard Protocol Analysis process is laborious and not suitable for real world projects. We utilised existing project development records in the form of meeting notes to investigate a long term project. The link extraction procedure is also simplified.

The three measures presented here are only a small sample of the existing and expanding social network research. By introducing SNA into design research we hope to expand the quantitative research tools that are available to the predominantly qualitative based discipline. At the same time we offer the
existing social network literature with fresh context to investigate and expand.

Endnotes

1. The procedure of the study was as follows: As a team member in the presented case study, the meeting minutes were taken by the First Author and recorded in a shared Google spreadsheet. Each team member was able review and edit the recorded meeting minutes. The minutes were available to be referred to during meetings. The analysis was conducted after the conclusion of the project. The link association was done by the First Author based the item description, assisted by personal recollections.

2. The SNA measures presented here are based on the set of R scripts developed by McFarland et al (2010).

Acknowledgements

The authors would like to acknowledge the Thermal Reticulations project (reported in the 2013 paper by Burry et al) and the project’s development team that form the case study for this paper, we would also acknowledge the technical support from Nathan Williams in the setting up of the link extraction system. This research was supported under Australian Research Council’s Integrating architectural, mathematical and computing knowledge to capture the dynamics of air in design funding scheme (project number DP130103228).

References


A. Published papers

A.3. Understanding social behaviors in the indoor environment: A complex network approach


Abstract

Extensive studies have shown that face-to-face interactions are a critical component in a work environment. It is an effective communication method that builds trust between team members and creates social ties between colleagues to ease future collaboration. In this paper we present our interaction analysis system that utilized an indoor tracking system to provide insights on the spatial usage and interaction dynamics in collaborative spaces. This gives space layout designers and managers quick feedback on the performance of the space and its occupancies and allows interventions and evaluations to be conducted to fine-tune the space layout or organization structure to achieve optimal performance. We demonstrate our system with data collected from a recent international design workshop.
Understanding Social Behaviors in the Indoor Environment: A complex network approach

Author Name
Mani Williams, Jane Burry and Asha Rao

Degrees, Position Title(s), Affiliation
Mani Williams, BE (Hons), MArch. PhD Candidate, Research Associate, Spatial Information Architecture Laboratory, RMIT University
Jane Burry, BA, Dip.Arch, PhD (AERB). Associate Professor, School of Architecture and Design; Director of the Spatial Information Architecture Laboratory, RMIT University
Asha Rao, BSc (Physics, Chemistry, Mathematics), MSc (Mathematics), PhD. Associate Professor, School of Mathematical and Geospatial Sciences, RMIT University

Keywords (up to 6)
Socio-spatial interaction, indoor tracking, interactions in collaborative design, complex networks, data visualization

Category
Practice-based and interdisciplinary computational design research

Summary (not exceeding 2 sentences)
A novel complex network interpretation of a set of indoor human-spatial interaction data recorded from an intensive design workshop to reveal the dynamics of social behaviors exhibited by designers in a shared studio environment.

Abstract
Being able to monitor and analyze human interactions in the indoor environment over time has many architectural applications from spatial planning to post occupancy evaluation. In this paper we present our interdisciplinary approach that interprets human-spatial interactions as a complex network. We combine methods and techniques from sensor networks, signal processing, data mining, network theory, and information visualization to form a novel framework that facilitates versatile investigations. We will demonstrate the framework with a real-world case study: we have collected and analyzed human-spatial interaction data from a workshop scenario where multiply design projects were conducted within a shared studio space.

Body text

1 Introduction
A network, in its simplest form, is a collection of discrete nodes joined by links. Originating in mathematical graph theory, the study and application of network theory has quickly grown into an interdisciplinary field with inputs from physics, biology, computer science, social
There has been a growing interest in understanding social interactions in the spatial context. Development of technology enables us to collect large quantities and variations of data, much of which is personally identifiable and geographically tagged. Individuals can be identified by their personal mobile devices and their spatial movement tracked through WiFi, Bluetooth and mobile network or GPS locations. This data can then be analyzed for behavior patterns within the wider social community (Dong et al., 2011, Holleczek et al., 2013).

Our research is conducted along similar lines of inquiry but at the architectural scale. At this scale we are dealing mainly with indoor environments. Compared with the openness of outdoor urban environments, indoor environments are cluttered with people, furniture and walls of various arrangement and composition that make accurate tracking a complex technical problem. The above mentioned tracking technologies that utilize existing infrastructure to provide urban scale tracking data are not easily adaptable to the indoors. At this scale active research focuses on developing applications of individual-spatial tracking technologies. Recent examples include a combined WiFi and GPS based mobile application to support university campus navigation (Biczók et al., 2014); a WiFi-based people behavior knowledge extraction system, to inform organizational facility planning in a hospital (Ruiz-Ruiz et al., 2014) and a Bluetooth-based visitor behavior monitoring system for spatial program management in a museum (Yoshimura et al., 2012). This paper contributes to this field of research by proposing a novel complex network-based approach to conduct effective socio-spatial analysis. We are utilizing the network’s focus on relative association rather than precise position to bypass the need for accurate positioning data. We will demonstrate the features and flexibility of our proposal with a case study.

2 Context and methodology

![Analysis Workflow](image)

In our study we examine the interaction between groups of people in a spatial context represented by a set of known locations. The data collection system is able to produce a list of records linking individuals to locations at certain times. At any given time this set of “who is at where” forms a (static) 2-mode network. Through network projection (Borgatti and
Everett, 1997) we can transform this network into two 1-mode networks, each representing the implied interactions between the people or the interaction between the locations. (Figure 1) When the data is collected over time, through the process of sampling we are able to construct a dynamic network representation of the changes in interactions.

We are interested in how people behave in a shared space. A university-based intensive workshop was selected as our case study. A group of students were divided into 3 projects that operated in the workshop. Over the course of 6 days they shared one studio space. This setup was intended to fertilize informal cross-project discussions. We recruited 14 participants for our study. They form a good representation of the overall organizational structure of the workshop. (Figure 2)

The data collection process consists of three components: a ZigBee-based indoor tracking system, a wireless time-lapse photography capture system and field notes from participant observation. The tracking and time-lapse data capture systems were automated (Figure 3); field notes taken were more ad hoc. This paper focuses on analyzing the data collected from the indoor tracking system (Figure 4) with reference to the photos and field notes when necessary.
The indoor tracking system is adapted from an off-the-shelf inventory tracking solution that utilizes the active scan and automatic mesh configuration functionalities of the ZigBee protocol to collect the spatial proximity data. Within the workshop space, 9 sensors were installed at locations of interest, with the locations being selected based on the expected spatial requirements of the projects. (Figure 5)
The tracking system was set up such that one tag could only be registered at one location sensor at a time, based on signal strength which is roughly correlated with proximity. Over a given time period this gave us a list of locations that each tagged individual has visited. We refer to this data as spatial interaction data. The tags were scanned at approximately 6 second intervals, resulting in 125063 tag-location data pairs over the 6 days of recording.
By processing the spatial interaction data with a certain set of criteria we are able to fine tune the behavior that we wish to observe. We first applied a 60 seconds moving low-pass filter on the raw data. (Figure 6) This was to remove the false negative records from incorrect location registration² as well as the false positive records from people who briefly walked past a sensor location en-route to their final destination. We divided the stream of spatial interaction data into 10 minute samples to convert the collected data into synchronous datasets for analysis. 10 minute intervals were selected as a reasonable approximation for the duration of an informal conversation. We further simplified the datasets by discarding duplicate entries within each of the time samples, producing a total of 2351 tag-location data pairs from 802 time samples, in which 431 time samples are non-empty.

We form our socio-spatial network by defining the 14 tagged individuals as the set of social nodes, with the 9 locations forming the spatial nodes of our network. The spatial interaction data are the links that connect the social nodes to the spatial nodes. For each time sample a static 2-mode social-spatial network was constructed from the spatial interaction dataset. The network becomes dynamic by letting the network structure evolve across time samples.

3 Analysis options
There are multiple strategies that can be used to interpret the socio-spatial network through a combination of qualitative and quantitative methods.

3.1 Quantitative method - Animated network visualization
We developed a network node placement algorithm to approximate the movement of the tagged individuals for visualization. The algorithm is a variation of the Fruchterman and Reingold layout (Fruchterman and Reingold, 1991), an iterative force-direct network visualization layout algorithm. The Fruchterman and Reingold layout algorithm was developed to use attraction and repulsion calculations to place network nodes for better visual perception of the network. To adapt the Fruchterman and Reingold layout we made the following adjustments regarding the treatment of the nodes:

- To better represent the effect of the spatial nodes on the social nodes, the spatial nodes were drawn to reflect the known spatial locations and kept stationary throughout the visualization. Position updates were only calculated for the social nodes.
- We assume that the movement of the people from one location to another is motivated by interest in something at the destination. In network theory terms the spatial nodes are responsible for the link creation, thus attraction calculations only originate from the spatial nodes. Repulsion force is calculated based on all nodes.
Figure 7: Network data visualizations of the 3 consecutive time samples (sample 46-48). Left: final placement of the social node showing links to the spatial nodes. Right: the transition effect from visualizing the intermediate iteration outcomes

For each time sample the placement was calculated over 50 iterations, with the attraction and repulsion forces exerting a small impact on the positioning of the (social) nodes. The parameters for step size, attraction and repulsion force impact factors are fine-tuned such that when the social nodes are visualized using the outcomes from the iterations it produces a transition effect that is effective in modeling the movement behavior of the people during the time sample. (Figure 7) Considering the number of time samples in this network,
the dynamic nature of the overall network is best viewed as an animated movie using the transition view of the time samples.³

As we gave the nodes color assignments that reflected the project assignment of the representing participants, overlaying the time sample's final placement gave us a good indication of the preferred work areas of the coordinator and the three projects. We can observe from Figure 8 that project 1 (green) favored the top left section of the room, project 2 (blue) worked mainly at the center tables and project 3 (red) stayed in the bottom right section. The coordinator (yellow) did not venture much into the working spaces of the three projects.

Figure 8: Overlaying node placement from all time samples
3.2 Qualitative method 1 - Social Network Analysis

Social Network Analysis (SNA) is the study of networks that represent social interactions through qualitative measures. To apply SNA to our data we projected the 2-mode socio-spatial network to a 1-mode social network projection: the subset of social nodes that are linked to one spatial node are now connected to each other and the spatial nodes are removed from the network. We selected 3 centrality measures (degree, closeness and betweenness; Freeman, 1979). This allowed us to analyze the social structure between the tagged individuals as presented by the social network (Figure 9 and Figure 10):

- **Degree** is the number of links connecting a node to the network. As it is calculated on the immediate network, it is a measure of the direct interactions a person had. For example a person with a low degree measure indicates this person worked more independently, whereas a person with a high degree measure interacted more with others.

- **Closeness** is the inverse of far-ness, which is in turn calculated as the total number of links a node required to reach all other nodes in the network. This makes closeness a representation of the central-ness of a person. A person with high closeness measure indicates that this person is more connected with the network thus more likely to have a better knowledge of the status of the workshop.

- **Betweenness** is a measure of one node’s criticalness on the overall reachability of the network. In our workshop context a person with a high betweenness measure would indicate that this person performed more of the role of a messenger and acted as a bridge between two otherwise separate groups.
Figure 9: Comparing the changes in SNA centrality measures between the tagged individuals across the duration of the workshop using the temporal view
Apart from presenting analysis outcome across time (temporal view, Figure 9) or summarize in an overview (Figure 10), the SNA centrality measures can be brought into spatial context by plotting using the placement derived from the animated network visualization algorithm. This gives us a spatial view of the social behavior that occurred in the workshop space. (Figure 11) The project-specific color coding allows us to perceive each project as an identity and focus on the distinct project behavior in the spatial context.
From Figure 11, we can see that the overall degree distribution is similar to the closeness distribution. This is due to the "thinness" of the network constructed from each time sample - the links between nodes are sparse and short. This means that in any 10 minute time sample the participants had a tendency to stay within the same group of people (the groups are not necessarily formed by people within the same project). In this case the spatial view of the betweenness measure is of most interest: when participants do interact between groups, where does it occur? Compared with projects 2 and 3, project 1 has a scattered distribution of the intergroup interactions, occurring not only in its home base but also into the preferred work area of the other projects.
Figure 12: The SNA centrality measures interpolate into heat maps

Each set of centrality measures can also be interpolated over the complete area of the workshop space to produce a heat map representation of the degree, closeness and betweenness distributions. (Figure 12) Interpolating the measures over the workshop space produces a more direct spatial perception of the distribution and intensity of the analysis results.
Figure 13: Two examples of the combined centrality visualization. Mimicking a person for easier interpretation, for each node the "head" represents the degree, the "body" represents closeness and the "diamond" represents the betweenness centrality measures. The combined centrality view improves the perception of the behavior differences between individual nodes.

For better visual perception of the social dynamic as it evolved with time, we recommend the combined centrality visualization where all of the three centrality measures are displayed together for each time samples. (Figure 13) This produces a set of visualization that can be presented as a storyboard or as an animation.

3.3 Qualitative method 2 - Complex network analysis

The SNA centrality measures offer a qualitative tool that gives an unbiased and simplistic analysis of the 2-mode socio-spatial interaction network based solely on the information presented in the network dataset. As we have demonstrated above, referring to the network node placement calculation we are able to incorporated spatial context into the analysis outcome.

In this section we present our work on new complex network analysis measures that are based on known “association” attributes of the network nodes. In this application we wish to analyze the effect of the project assignment on the individuals as well as the workshop spatial allocation on the interactions. To do this we have introduced the “group” (in our case the assigned project) attribute to spatial and social nodes. In the previous diagrams we have already incorporated the group attribute in our discussion through the qualitative method of
color labeling. Through our proposed complex network analysis measures we quantitatively analyze the preferences of the individuals regarding their movement between locations.

We propose the following mobility analysis measures (Figure 14 and Figure 15):

- **Individual measures:**
  - “A” or the “at home base”: This calculates how often one individual was at the locations assigned to his/her group.
  - “a” or the “away”: This is opposite to at home; we are interested in how often one individual was presented at the locations not assigned to his/her group.

- **In-group activity measures:**
  - “AA” or the “home meeting”: This is the measure of the in-group activity that occurred at locations assigned to the group. We assume when two individuals from the same group met, they were conducting in-group activities.
  - “aa” or the “away meeting”: This is the opposite to home meeting, and is concerned with group activities that occurred at locations not assigned to the group.

- **Out-group activity measures:**
  - “Ab” or the “receiving meeting”: While the individual was at home how often he/she was visited by a member from another project.
  - “aB” or visiting meeting”: This measures how often one individual visited the work areas of other projects and met with the members of the other projects.
  - “ab” or “neutral meeting”: This is how often one individual met with people from another project at a location that was assigned to neither person (neutral grounds).
Figure 14: Diagram explaining the seven mobility analysis measures

A

An individual working in the project's allocated space

a

A individual working away from his/her project's allocated space

AA

A group from the same project are at their project's allocated space

aa

A group from the same project are away from their project's allocated space

Ab

An individual met a member of another project at former's project's allocated space

aB

An individual met a member of another project at latter's project's allocated space

ab

An individual met a member of another project at a neutral space
This set of measures is useful in comparing the working style between individuals and projects. For example, reading Figure 15 we can see that compared with other projects, the members of Project 2 (red), apart from the project leader (dark red), tend to work within their own assigned space (high *at home* measures). Two of these individuals (P2a and P2b) worked closely together (high *home meeting* measures), whereas P2c worked with people from other projects but still within project 2’s assigned space (low *in-group activity* measures but high *receiving meeting* measure). Their project leader (P2) appears to have worked differently: he/she worked away from the project (low *in-group activity* measures and *receiving meeting* measure) but closely with member(s) of other project(s) (high visiting meeting measures).
Also note that the *in-group activity* measures are not applicable to P0 (the workshop coordinator) as he/she did not have any group members.

Specific information about the workshop interactions can be revealed through query-driven visualization and analysis. Here are a few examples.

### 3.3.1 Coordinator’s queries

The workshop coordinator may wish to get a feeling of how the workshop has progressed as a whole:

- "Did the participants socialize much and mingle with people from other projects?" - Visualize the combined out-group measures (Ab+aB+ab).
- "Were neutral spaces required often for these occasions?" - Visualize the out-group neutral meeting measure (ab).
- "How were the collaborations within the projects?" - Visualize the in-group meeting measures (AA+aa).

Through the temporal view (Figure 16, top) we can see that the workshop participants socialized regularly, and the spatial view (Figure 16, below) shows that interactions between groups were well distributed in the workshop space. This meant that the intention of the workshop leaders “to fertilize informal cross-project discussions” was successful.

Meetings between projects on “neutral grounds” occurred sparsely, and looking at the spatial view it occurred mostly at the center of the workshop space around the coordinator’s desk. We suspect these meetings were facilitated by the group members that the spaces were assigned to (such as the coordinator at the coordinator's desk).

Collaboration within the project occurred intensively in the first three days of the workshop. From the fourth day project 2 and 3 seems have changed working structure. To understand this better we put together another diagram of mobility measures of the three projects (Figure 17). From this diagram we could see the drop in recorded collaboration within project 2 and project 3 was actually because the majority members from these two projects were not recorded present in the workshop space.

### 3.3.2 Project leader's query

A project leader may wish to see the work pattern of the project members. Here we show the seven mobility measures for three members of project 1. We can see that these three participants had similar *in-group* work pattern, and from comparing the *out-group meeting measures* it shows that project leader P1 conducted most of the inter-project activities.
Figure 16: Coordinator's queries
Figure 17: The mobility of the projects: Home (A - fill) versus Away (a - no fill)
Figure 18: Work pattern of the individuals from project 1
4 Discussion

A network is a flexible and versatile data representation structure that allows multi-focused analysis at different scales, from the large scale overview of the workshop activities to the small scale study of the immediate contact of a person. With additional attributes we can further study the impact the known contextual information, such as organization arrangement, spatial setup and workshop scheduling, had on the behavioral network.

Validity of the network analysis is sensitive to the change in sample size and the appearance of sample holes (Costenbader and Valente, 2003). The analysis results should not be used as the sole evidence to evaluate the workshop dynamics. It is important to interpret the data analysis outcome with reference to case-specific contextual information (such as participant observation data, interviews, schedule of activities and past experience). In our study factors such as the planned workshop excursions on day 4, and many participants deciding to work from home on day 5 to 6 because it happened to be a weekend all influenced the appearance of the low activity level presented by the data analysis. Further work to develop a comprehensive visualization and reporting system that incorporates schedule, field notes and photos will improve the validity and comprehension of the results. The event-based model proposed by Simeone and Kalay (2012) is also an interesting alternative to incorporate additional context from field notes and high level activity recognition from the time-lapse photos.

Participant consent, privacy and participation rate are interlinked issues in tracking and in network studies (Borgatti and Molina, 2003). Pervasive technologies such as WiFi and Bluetooth based systems improve user participation and retention by linking tracking activity with an object or service that people require, but the ethical issues of participant consent and equality of these systems are often overlooked (Luger and Rodden, 2013). With standalone systems such as RFID and ZigBee based tracking systems the consent process is much clearer; people can easily remove themselves from the set up by detaching the tags from their person. We believe this feature actually helped us to persuade participants to sign up. In contrast to other large scale ethnographic studies, network studies are based on the direct links between its individual participants. The familiarity of the participants to each other meant that even with the results anonymized, individual identities can still be easily deduced by people familiar with the context study. A comprehensive discussion on the topic of open data is beyond the scope of this paper. The contribution of our paper is that we have demonstrated that our proposed framework is can be used by and for all stakeholders of the study. With this incentive we hope to persuade potential participants to join and be part of similar studies in the future.

5 Conclusion and future work

This paper presented a complex network-based approach to analyzing and visualizing socio-spatial interactions in the indoor space. The versatility of the approach has been demonstrated with a range of qualitative and quantitative methods applied to a real-world case study. In addition to adapting existing network analysis measures we developed an animated network
visualization algorithm and a set of complex network measures to analyze the network interactions based on known group attributes.

We propose that our approach is the basis of a comprehensive tool for project management or post-occupancy evaluation applications. We have already demonstrated with our workshop case study that stakeholders of the project benefit from the proposed analysis of the project dynamics. These insights are useful in collaboration projects where the organization/communication structure is less defined and fluid.

Further work is planned to incorporate the algorithms and analyses presented in this paper into a versatile visual analytic system, based on needs and access level, targeted visualization view will be set up for different roles. Through interacting with the system project managers and other stakeholders would able to have an live update of the progress of the project. Post-occupancy evaluation applications can also benefit from such a the system. For instance space designers and building managers can use the system to monitor and iteratively improve the spatial usage of the building, evaluate it against planned occupancy, and observe its impact on occupants’ work performance or social behavior.

**Image Captions**
Figure 1: Analysis Workflow
Figure 2: The organizational structure of the 14 tagged individuals (left) and their roles in the workshop (right)
Figure 3: Automated data collection set up
Figure 4: 3D representation Individual’s workshop activity as recorded by the ZigBee system
Figure 5: Workshop space with project assigned spaces highlighted with different colors
Figure 6: Moving filter
Figure 7: Network data visualizations of the 3 consecutive time samples (sample 46-48). Left: final placement of the social node showing links to the spatial nodes. Right: the transition effect from visualizing the intermediate iteration outcomes
Figure 8: Overlaying node placement from all time samples
Figure 9: Comparing the changes in SNA centrality measures between the tagged individuals across the duration of the workshop using the temporal view
Figure 10: Overview of the SNA centrality measures between the tagged individuals
Figure 11: The three SNA centrality measures presented in the spatial view
Figure 12: The SNA centrality measures interpolate into heat maps
Figure 13: Two examples of the combined centrality visualization. Mimicking a person for easier interpretation, for each node the "head" represents the degree, the "body" represents closeness and the "diamond" represents the betweenness centrality measures. The combined centrality view improves the perception of the behavior differences between individual nodes.
Figure 14: Diagram explaining the seven mobility analysis measures
Figure 15: The seven mobility analysis measures applied to evaluate the overall project related behaviors
Figure 16: Coordinator's queries
Figure 17: The mobility of the projects: Home (A - fill) versus Away (a - no fill)
Figure 18: Work pattern of the individuals from project 1

Endnotes:
1 Indoor Tracking system v2.0, manufactured by DTK Electronics, Shenzhen, China. Product listing URL: http://www.dtkcn.com/
2 During laboratory testing the ZigBee system was found to provide an average tracking performance of 79% True Positives when recording transition between 2 sensors placed 10 meters apart. For more information on the data collection set up and testing procedure please sees Salim, Flora et al. (2014).
3 A video of the animation transition view can be found from https://vimeo.com/99713412
4 The animated video of compare three network visualizations can be viewed at https://vimeo.com/98091919
5 See the review of data capture techniques in Yoshimura, et al., (2012).
6 A recurring question asked by potential participants was "will it track me when I go to the bathroom".

The authors wish to thank Dr. Flora Salim, Daniel Prohasky, Philip Belesky, and participants of the Sense and Sustainability workshop from RMIT, Melbourne, and Universitat Politécnica de Catalunya (UPC), Barcelona, for their support and contribution to the case study reported in the paper; we also thank Karin Hofert and Eloi Coloma from UPC for giving us the permission to conduct data collection on the UPC ETSAB campus. We wish to acknowledge the technical contribution from Nathan Williams, the EnviS team and the Attractors Project in the setup of the data collection system. This research was supported under Australian Research Council's Integrating architectural, mathematical and computing knowledge to capture the dynamics of air in design funding scheme (project number DP130103228).

Works Cited


Salim, Flora, Mani Williams, Nishant Sony, Mars Dela Pena, Yury Petrov, Abdelsalam Ahmed Saad, and Bo Wu. 2014. “Visualization of wireless sensor networks using ZigBee's Received Signal Strength Indicator (RSSI) for indoor localization and tracking.” Paper presented at the 2014 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops), Budapest, Hungary, March 24-28.

Williams, Mani. 2014. “Force-directed transition view vs photo footage.”  

Williams, Mani. 2014. “Three versions of the force-direct node-placement visualisation.”

Author Bio

Mani Williams is a PhD Candidate and Research Associate in the Spatial Information Architecture Laboratory (SIAL), RMIT University. Mani has a multi-discipline background of engineering, mathematics and architecture. Her current research interest is in adapting and extending current complex network theory to reveal the dynamics of social interactions. She has published international papers in the areas of digital design, design studies, ubiquitous computing and image processing.

Jane Burry is an architect and Associate Professor in the School of Architecture and Design, RMIT University, Melbourne, Australia. Jane directs the Spatial Information Architecture Laboratory (SIAL), a transdisciplinary design research laboratory and is program director for the Master of Design Innovation and Technology. Her research focus is mathematics in contemporary design. Jane is lead author of The New Mathematics of Architecture, Thames and Hudson, 2010. She is also engaged in research into the relationship between architecture and advanced manufacturing, and the integration of analysis feedback in early design and its intersection with interactive physical and digital architecture (Designing the Dynamic, Melbourne Books, 2013). She has over sixty publications and has practiced, taught and researched internationally.

Asha Rao is an Associate Professor in the School of Mathematical and Geospatial Sciences, RMIT University. Her research interests include applying algebraic techniques to communications, coding and information theory, the study of complex networks, management and standardization issues relating to information security policy. She has published many technical journal articles as well as, more recently, articles on the application of risk management techniques to tackle money laundering.
A. Published papers

A.4. A system for tracking and visualizing social interactions in a collaborative work environment

©2015 The Society for Modeling & Simulation International (SCS). Reprinted, with permission


Abstract

This paper presents our work on indoor tracking and demonstrates its capacity as a data collection system for the study of socio-spatial interactions that occur in a collaborative work environment. Deployed at a recent week-long international design workshop, our system was able to track the movements of more than fifty people from various roles, and generate live visualizations. In this paper we will present the data collection system and the system configurations, the complete dataset collected and sample visualization scripts to stimulate further research in the area of people interaction study and its relation to spatial usage.
A System for Tracking and Visualizing Social Interactions in a Collaborative Work Environment

Mani Williams
Spatial Information Architecture Laboratory
RMIT University
Melbourne, Australia
mani.williams@rmit.edu.au

Jane Burry
Spatial Information Architecture Laboratory
RMIT University
Melbourne, Australia
jane.burry@rmit.edu.au

Asha Rao
School of Mathematical and Geospatial Sciences
RMIT University
Melbourne, Australia
asha.rao@rmit.edu.au

Nathan Williams
Qinlao Designs
Melbourne, Australia
nathan@qinlaodesigns.com

ABSTRACT
This paper presents our work on indoor tracking and demonstrates its capacity as a data collection system for the study of socio-spatial interactions that occur in a collaborative work environment. Deployed at a recent week-long international design workshop, our system was able to track the movements of more than fifty people from various roles, and generate live visualizations. In this paper we will present the data collection system and the system configurations, the complete dataset collected and sample visualization scripts to stimulate further research in the area of people interaction study and its relation to spatial usage.

Author Keywords
Indoor tracking; behavior modeling; data visualization; collaboration; design workshops.

INTRODUCTION
The study of social interactions has many applications including organizational management, post occupancy evaluation and occupant behavior modeling. The widely used ethnographic methods of data collection such as participant observation, interviews and questionnaires are labor intensive and require experience and expertise to properly execute and process into quantifiable datasets. With the rise in digital communications, researchers now have relatively easy access to vast amounts of social data from social network platforms as well as from tracking personal devices [1]. In the physical spaces, especially the indoor environment, there is still an active area of research in sensor systems and applications in developing systems to accurately capture human movements [2]. This paper extends current work in this area [3-6] by presenting the technical specifications of our deployable system that is capable of collecting social data in the built environment in an automated and minimally intrusive manner. We aim to present the system in a format that is easily replicable and adaptable by others that are interested in conducting research on indoor people behavior. The data collected from this system is supported by a set of fixed cameras that collect time-lapse photography of the space.

In this paper we will present an overview of the technical details of the equipment and the data collection setup, demonstrate the functionalities of the system using sample data and visualizations, as well as recommendations on how to implement our setup at other venues and events. The dataset and sample visualization script are included with this paper [7].

EQUIPMENT AND SETUP
The setup used in this project is categorized into two sub-systems: indoor tracking and time lapse photography.

Indoor tracking
The indoor tracking system is composed of an off-the-shelf ZigBee-based indoor location system, a Raspberry Pi-based local database and an automated visualization interface hosted on Amazon Web Services (AWS).

The ZigBee-based indoor location system includes a set of tracking tags, a set of beacons and a data module. The tagged participants attached the tracking tags to their nametag lanyards. The beacons and the data module require external power. The location system modules communicate to each other wirelessly via the ZigBee mesh protocol [8]. The ZigBee protocol supports auto configuration between devices, giving greater system adaptability and flexibility: we could rearrange the beacons and introduce new participants into the system with ease. The ZigBee data module periodically outputs the tag locations via an Ethernet connection using the UDP protocol, targeted to a specified IP address and port number.

The Raspberry Pi-based data collection system (to be referred to as the data collector) is a single board computer running the Raspbian operating system (a Linux distribution optimized for the Raspberry Pi hardware). We set up the system with the required IP settings and connected it to the same local area network (LAN) as the ZigBee data module. It listened on the specified UDP port number to capture the location data as the ZigBee data module transmitted it. The data was then stored on a
MySQL database, with the current computer time taken as the data time stamp. This LAN setup allowed us to place the ZigBee data module at an advantageous position inside the wireless mesh network and away from the Raspberry Pi, which required easy access for maintenance. A time-based script was scheduled on the Raspberry Pi to synchronize the local database with a remote database.

Due to its limited processing power, a Raspberry Pi computer could not reliably handle stream data capturing and advanced data processing on the same device. An AWS EC2 instance running Ubuntu Linux was set up as the cloud computer to handle live data analysis and visualization. A MySQL database was set up and periodically synchronized with the onsite database. We installed R and a collection of R libraries to conduct primary data analysis and generate visualizations. This will be described in detail in the later section of the paper. A t2.micro EC2 instance was found to be sufficient to process and generate the visualizations at scheduled one-minute intervals. The visualizations were publically accessible via a website hosted on the EC2 instance.

**Time-lapse photography**
A set of Raspberry Pi-based IP cameras was configured to capture photographs of the areas of interest. It utilizes the Raspberry Pi camera module, and can be configured to capture an image on command or at preset intervals. Each was installed on the ceilings of the spaces with a view to cover an activity area. This provided us with a good visual record of the activities that occurred in these spaces.

![Figure 1 Floor plan of the main workshop spaces monitored by the tracking system](image1)

<table>
<thead>
<tr>
<th>Tag</th>
<th>Time</th>
<th>Reason 1</th>
<th>RSSI 1</th>
<th>Reason 2</th>
<th>RSSI 2</th>
<th>Reason 3</th>
<th>RSSI 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>HEX 4</td>
<td>2019-01-01 12:00</td>
<td>4 hours</td>
<td>50</td>
<td>2 hours</td>
<td>60</td>
<td>4 hours</td>
<td>70</td>
</tr>
</tbody>
</table>

**DATA COLLECTION**

The data collection was conducted at a recent international design workshop. The workshop was held over five days with an exhibition on the evening of the last day. Several projects operated within the workshop. Each project consisted of project leaders, participants and technical supporters. Throughout the five-day event, the workshop occupied the entrance, atrium space and a large proportion of a floor of an educational institution building. The spaces were mostly open, allowing the workshop organizers to vary the amount of the space assigned to individual projects as needs arose.

Thirteen beacons were installed at the beginning of day two and an additional nine beacons were installed on day four, with configurations as shown in Figure 1. We placed the beacons regularly around and above the activity spaces to get good coverage of the activities. This covered the atrium and project areas on the main workshop floor level; these were occupied by the eight workshop projects and the workshop organizers’ desk. Participation in the tracking experiment was voluntary; fifty tags were distributed to the workshop attendees, this included representatives from all of the eight projects that occupied the floor as well as several of the workshop organizers. Additional tags were placed in the tracking zone for evaluation use. The tracking system recorded data from the start of day two to the end of day five. The location system was configured such that when a tag was detected to be within range, it collected the ID and the received signal strength indication (RSSI) from the three strongest beacon signals and output a data entry via the ZigBee data node. A timestamp was added by the data collector. Figure 2 shows the final data format.

The dataset published with this paper includes:

- the raw tracking data recorded from the ZigBee location system;
- a floor plan of the workshop area;
- the coordinates of the beacons in relation to the floor plan;
- a list of the tags, noting the project or activity they were associated to (labeled as ‘group attributes’.)

The IP cameras were installed to cover each of the project activities, in operation from the start of day one to the end of day five. We configured the cameras to take a long exposure image at five-minute intervals. This was to produce a blurred image that captured the dynamics of the activities, and also had the additional advantage of giving privacy to the workshop participants. The photos are not part of the dataset that is published with this paper, but we have produced a set of videos from them which can be viewed from the Author’s website [9].

![Figure 2 Tracking data stored format](image2)
Figure 3 Sample live data visualizations produced from ten minutes of data. Top: Time plots and spatial plots for an individual tag, showing individual’s movement path. Bottom: Combined overview of all tags in the space, showing group spatial preference.

Group behaviors
We collected information on the activities that the tagged individual were involved in, which allowed us to assign group attributes to tags. By assigning colors to the group attributes we can start to represent and visually identify the group behaviors.

Taking a one hour sample from the dataset, we separated the sample by the data entries tag group attributes and plotted each group onto the floor using the tag position estimates (Figure 4). We could see that in this hour the workshop coordinators (SG) and hosts (CUHK) visited different projects. Between the eight tracked projects (PM, SE, RN, DS, FB, ST, DSE and Block) we could also observe distinct behaviors: PM appeared to be operating from two spaces, FBR was more mobile and Block was absent during that hour.

DISCUSSION
As with any project involving humans, it was very important for us to conduct this project in an ethical manner. Specifically we sought ways to protect the participants from harm and encourage participation through engagement:

- Voluntary participation: We selected the ZigBee based system as the tracking tags are self-contained; this allows the participants to easily detach the tag from their person if they do not wish to be tracked for a period of time. We believe this is less intrusive than other tracking systems that rely on personal devices (such as WiFi or Bluetooth based systems)
- Transparency and participant engagement: By producing live data visualization the people were more comfortable with the idea of been tracked. After recruiting the initial set of participants, we had people approach us to be tagged because they have seen or heard from others of the data visualizations. Participants also came to us with unplanned requests such as asking us to help to locate a bag and increase time-lapse photograph frequency to help document their project.

Positive engagement also extends to the workshop organizers and hosts. During the project planning stage the host was actively contributing to the selection of the locations for beacon and camera installation. Communication with the workshop organizers allowed us to more accurately plan the quantity of equipment required. The support from the organizers and host eased the installation and recruitment process.

Known system limitations
We estimated the spatial accuracy of the tracking data to be between 1 to 2 meters. This is highly dependent on the spatial context: such as the presence of people, furniture placements, and surface materials; this is a known issue with RSSI-based indoor tracking systems operating at
2.4GHz. We are conducting ongoing research to improve tracking accuracy using data processing methods. The data collection Raspberry Pi performs database backup and remote synchronization at five-minute intervals, which minimizes data loss. We also noticed issues with data drop: when the data collector lost internet connection the system hangs for approximately 45 seconds at each scheduled synchronization job. These issues could be resolved with a better system design.

With reference to the time-lapse we observed instances of tags left behind overnight. It is also known that some participants kept the tag in bags. We are currently developing data mining methods to identify the idle tags and remove them from the dataset. This is still a work in progress; from the reference tags placed in the space we have data on the “appearance” of idle tags. In the tag list included in the dataset we have included descriptions of the reference tags, and we welcome external collaboration on this topic.

We are also working on modeling interaction behavior based on (a) personal proximity extracted from the position estimates and (b) people-spatial interaction interpreted from the tag-beacon data entries. We see the methods developed from this research applicable to other tracking setups and contexts. Figure 5 shows some of our preliminary results.

ACKNOWLEDGMENTS
The authors would like to thank the participants of the SmartGeometry2014 Workshop for their support and contribution to the case study reported in this paper; we also thank the SmartGeometry Group and the Chinese University of Hong Kong for giving us the permission to conduct data collection. This research was supported under Australian Research Council’s Integrating architectural, mathematical and computing knowledge to capture the dynamics of air in design funding scheme (project number DP130103228).

REFERENCES

Figure 5 Examples of the application of the social interaction data. Top: One group's interaction network constructed based on proximity analysis of the group members’ tag locations. Right: Overall event interaction network. Bottom: Event interaction heat map.
A. Published papers

A.5. Graph mining indoor tracking data for social interaction analysis

©2015 IEEE. Reprinted, with permission

Mani Williams, Jane Burry, and Asha Rao (2015a). “Graph mining indoor tracking data for social interaction analysis”. In: Pervasive Computing and Communication Workshops (PerCom Workshops), 2015 IEEE International Conference on. IEEE, pp. 2-7

Abstract

With the advancement in wireless sensor networks (WSN) researchers in social network analysis (SNA) now have access to larger and more complex datasets that describe human interactions in the physical space. Studies in WSN thrive on accuracy and robustness whereas SNA operates on a higher level of data abstraction. Graph mining is a bridge between these two fields. This paper investigates two approaches to graph mining and compares their efficiency and appropriateness as the input systems for a social interaction analysis process.
Graph Mining Indoor Tracking Data for Social Interaction Analysis

Mani Williams and Jane Burry
Spatial Information Architecture Laboratory
School of Architecture and Design
RMIT University
Melbourne, Australia
Email: {mani.williams, jane.burry}@rmit.edu.au

Asha Rao
School of Mathematical and Geospatial Sciences
RMIT University
Melbourne, Australia
Email: asha.rao@rmit.edu.au

Abstract—With the advancement in wireless sensor networks (WSN) researchers in social network analysis (SNA) now have access to larger and more complex datasets that describe human interactions in the physical space. Studies in WSN thrive on accuracy and robustness whereas SNA operates on a higher level of data abstraction. Graph mining is a bridge between these two fields. This paper investigates two approaches to graph mining and compares their efficiency and appropriateness as the input systems for a social interaction analysis process.

I. INTRODUCTION

By tracking the physical proximity of people with their surrounding environment over time through the use of wireless sensor networks (WSN), we can gain insight into the development of the group dynamics in the physical environment[1], [2], [3], [4], [5], [6], [7]. At the system level the proximity-based WSN can be divided into two operation types (Fig. 1). We can either infer the social interactions directly through the use of mobile proximity sensors; this person-person proximity setup produces a log of physical distance between tagged individuals from which a dynamic social network can be generated [8], [7]. The other option is the location-person WSN setup where an additional set of reference sensors are used. The data logged are between the tags and the reference sensors (commonly known as beacons). This allows the additional contextual attributes (such as spatial coordinates and events) [3] to be collected for the mobile tags. There exist social interaction mining solutions that use a combination of the above proximity options [2], [5] as well as support the proximity data with other sensors such as environmental sensors[1], microphones, accelerometers among others[6], [9], [10]. Although the multimodal inputs help to paint a more comprehensive picture of the interaction dynamics, this may not be possible in all cases due to privacy, technical and other limitations. Adapting and fine tuning the social interaction graph mining processes to utilise solely the location-person WSN data is the focus of this paper.

Graph mining for social network analysis is a process that transforms isolated data entries into interdependent person-person relationships. It consists of removing outliers (in our case idle tracking tags) and then extracting relationship links based on a set of parameters. In this paper we present two distinct graph mining processes: a signal processing based graph mining approach and a network based graph mining approach. We draw upon existing methods to construct the two processes. In the following sections we will first explain the two processes in detail, and then demonstrate their capability and flexibility by applying them to a set of real world tracking data we collected. We conclude this paper with a comparative evaluation between the two processes and discuss their application as a graph mining process for social interaction analysis.

II. SIGNAL PROCESSING (SP) GRAPH MINING

The intuition of the signal processing based approach is to process the tag data independently before performing association analysis to convert it into tag-tag pairwise links for further social network analysis (SNA) (Fig. 2).

Our signal processing based link mining approach consists of the following stages:

1) Divide the input data stream into sets identified by the tag ID.
2) Collect the datasets over a given time period.
3) For each tag dataset:
   a) Map each data entry to the spatial domain by calculating the X, Y coordinates estimated from the beacon receiver signal strength indicators (RSSI).
Fig. 2. SP approach graph mining: mapping data entries to X, Y coordinates (i), determining activity areas (ii), identify idle tags (tag A) and perform link extraction based on the activity centres of the tags (iii)

b) Perform multivariate analysis [11] on the X, Y coordinates to determine the tag’s activity centre (the cluster centre of the X, Y coordinates) and active area (the area of the polygon that contains a certain percentage of the inner points).

c) Perform tag idle detection by comparing the tag’s active area with a predetermined threshold

4) Construct an association matrix by calculating the spatial distance between the tags’ activity centres.
5) Apply an appropriate distance threshold to extract tag links.
6) Construct a social graph.

There are several variables that impact on the output social graph.

- The data sample time period should be determined in consideration of the types of social behaviours that we wish to examine. For example a short sample size of 10 minutes can be used to capture informal social exchanges, whereas for technical collaborations a one-hour-long window may be more appropriate. It is also possible to combine links from multiple consecutive time samples to generate a weighted graph.

- Outer points removal rate is applied to the cluster of estimated X,Y coordinates to remove a proportion of the outer points. We found the polygon area that contains the inner cluster points gave a more robust indication of the activity level of the tag. We have tested this method against the autocorrelation method, and the entropy method and found that the our method was more reliable in identifying the idle control tags from the sample dataset.

- The idle tag area threshold distinguishes mobile tags from stationary tags by the area travelled determined from the inner cluster’s X, Y coordinates. This should be determined by the accuracy of the tracking system and the signal interference from the environment. It should be sensitive enough to separate tags that were carried by people with those that were left behind (i.e. on the table), but robust enough to detect the change in signal quality caused by the daily activities in the space.

- The cluster centre distance specifies the closeness of two tags’ activity centres needed to constitute a link. Similar to the data sample time period, the interaction type, specifically the physical setting should be considered: for example the diameter of a cluster of tables would be a good threshold to extract teamwork collaborations.

III. COMPLEX NETWORK (CN) GRAPH MINING

A network is a graph structure consisting of a set of nodes and a list of links that connect them. A network is known as bipartite when there is a distinction made that separates its nodes into two sets and only allows links connecting nodes from different sets. The motivation behind the complex network approach is to consider the tracking system as a bipartite network where the two node sets are the tracking beacons and the tags, links between the two node sets are the data entries. Idle tag detection and the data reduction process are handled through network manipulation (Fig. 3).

The proposed network based graph mining approach consists of the following stages:

1) Collect data entries over a given time period.
2) Construct a link-weighted bipartite network where the node sets are the sets of beacons and tags, links between the tag and the beacon are created by the data entries, with the weight corresponding to the number of occurrences.
3) Any tag that has an unweighted degree below a predetermined threshold is identified as an idle tag and is removed from the network.
4) Noise filtering is done by removing a percentage of the weaker links for each of the active tags.
5) Compress the network into an unweighted network by dropping link weights.
6) Project the bipartite tag-beacon network into an unweighted unipartite network of tag nodes, where nodes linked if they have at least one common beacon node.

There are several variables that impact on the output social graph:

- Similar to the signal processing based approach, the data sample time period controls the duration of the activities that we will be studying.

- In an ideal environment a tag that has remained in a beacon’s strength coverage should only be registered with that one beacon. Due to the complex nature of a real world environment, factors such as furniture material and placement, the tag’s placement on the human body and people movement all influence the
signal strength between the tag and surrounding beacons. Compared with an idle tag, a tag worn on a person has the additional interference coming from the movement of the wearer. The idle tag beacon count threshold should be determined to take advantage of this fact.

- Similar to the signal processing approach’s outer point removal rate, we can vary the weak link removal rate to manage data noise as well as focus the analysis towards the more frequent beacon-tag relationships.

When determining which approach to implement there are several factors to consider: such as accuracy, efficiency, memory requirement and processing time. Our goal should not be pursuing the best in every aspect but to find the combination that is appropriate for the scenario in the study. We shall use a real world case study application to demonstrate.

IV. CASE STUDY

We collected data at a recent design workshop. The workshop was attended by students and professionals from the design industry, based on a collaborative teamwork framework where the attendees formed into several project teams. The collaborative workshop event aimed to encourage positive interaction within the teams to work towards a common project outcome as well as to stimulate interactions between teams to exchange ideas and skills and foster new social, professional and academic connections. For the workshop organisers it would be advantageous to be aware of interpersonal face-to-face interactions that occurred during the workshop.

A. WSN data input system

The Wireless Sensor Network tracking system we used consisted of a set of proximity beacons and tags based on the ZigBee technology [12]. The beacons and tags are preset with the same mesh network configurations. Each tag is battery powered and automatically joins the ZigBee mesh when it is in the range of one or more beacons. This tag periodically queries the network for the presence and signal strength of tracking beacons. For each query it will rank the detected beacons by the receiver signal strength indicator (RSSI) and output a data pack containing its own tag ID and a pair of the beacon ID and RSSI data of the first (in the basic mode) or the top three beacons (in the extended mode). The data pack is then logged in a SQL database with a time stamp.

Through testing, the system was found to provide an average tag-beacon registration performance of True Positives (TP)=79% when recording the transition between two beacons placed 10 meters apart, using two tags (Fig. 4). The signal strength (RSSI) was tested over a distance of 20 meters to a beacon. As seen in the signal strength test results, the signal strength outputs are an unreliable representation of the precise distance, as they are sensitive to the placement of obstacles (such as people, furniture and fixtures). In the SP approach the RSSI values were used to estimated tag position: the tag position estimates were calculated as the mean X, Y coordinates of the three strongest beacons’ coordinates, weighted with the corresponding beacon RSSI readings. The RSSI values were not used in the CN approach.

![Fig. 4. WSN performance testing: delivered an average tag-beacon registration performance of True Positives (TP)=79% when recording the transition between two beacons placed 10 meters apart, using two tags.](image)

![Fig. 5. WSN performance testing: RSSI testing of two tags tested over a distance of 20 meters to a beacon.](image)

B. The Context

There were nine collaborative project teams tracked in this experiment. The teams shared the overall workshop space. At the start of the workshop certain spaces were allocated to each team. As the workshop progressed teams negotiated for more resources or exchanged with other teams. In this experiment the extended WSN mode was used with query rate set at 3 seconds. Twenty-two beacons were installed in the configuration shown in Fig. 6 Fifty tags were distributed to the workshop attendees with additional tags placed in the tracking zone for evaluation use. Two of the authors attended this workshop, one as a workshop organiser another as project leader. This allowed us to experience the workshop firsthand, although we could not be everywhere at once, we could still make certain judgements on the results.

To demonstrate the analysis we have taken an hour-long sample between 14:00 and 15:00 on the fourth day of the workshop. The one hour sample has been subdivided into two thirty-minute samples and six ten-minute samples to evaluate the effect of sample durations on the link mining outcomes. For visual clarity, the tag data and analysis visualisation are coloured according to their project team attributes.

C. Variables for the signal processing approach

As introduced in section II, there are three signal processing specific variables that need to be considered: outer points removal rate, idle tag area threshold, cluster centre distance threshold. Considering the context, we have implemented the test values in Table I.
D. Variables for the Complex Network Approach

The complex network approach has two variables: the idle tag beacon count threshold and the weak link removal rate. The values in Table II are implemented for evaluation.

V. COMPARATIVE EVALUATION

As the two approaches depend on different set up variables, it is best to examine their performance within the context of a specific social interaction. Next we suggest two targets of social interactions to examine: casual social interactions and close proximity collaboration interaction.

A. Focus on casual social interaction

We shall interpret casual social interaction as a short interaction between two people that occurred when they met unscheduled, for example two friends who met on the stairs and stopped to inquire after each other’s project. We select the use of the ten-minute data samples. For the signal processing approach we applied the high outer point removal rate of 75%, this combined with a higher idle tag area threshold of 2 square meters placed a focus on people that are mobile. A moderate cluster centre distance threshold of 4 meters was set to capture interactions at this distance. With the complex network approach we set the idle tag beacon threshold to 4 to focus on mobile people and used a moderate weak link removal rate of 50%. When applied to the six consecutive ten-minute samples we produced the social graphs shown in Fig. 7. The comparative evaluation results are shown in Table III.

B. Focus on project collaboration

We interpreted project collaboration as two people situated close to each other for a long duration of time, for example sitting side by side working together on a digital model on one person’s laptop. For this we used the two sets of thirty-minute samples. For the signal processing approach we applied the moderate outer point removal rate of 50%, but tightened the idle tag area threshold to 1 square meter to focus on people that are stationary while still removing idle tags. A smaller cluster centre distance threshold of 2 meter was set to capture the more intimate physical integration distance. With the complex network approach we set the idle tag beacon threshold to 1 and used the high weak link removal rate of 75%. When applied to the two consecutive thirty-minute samples, the resulting social graphs can be seen in Fig. 8, comparative evaluation in Table IV.

It is a fair assumption that interactions between participants from the same project team were likely to be collaboration focused, and interactions between participants of different projects were more social. Comparing the two sets of variable settings (Table IV), the collaboration interactions settings for both approaches are able to extract more group links (% link made within project measure) than the social interaction settings outcomes (Table III). This can also be observed from the coloured tag nodes in the social graphs: the social interaction settings created social graphs with connected components that are from different project teams (Fig. 7), whereas the collaboration interactions setting created components that are more likely to be within the same project team (Fig. 8).
TABLE III. THE PERFORMANCE COMPARISON OF THE TWO APPROACHES IN GENERATING SOCIAL GRAPHS OF CASUAL INTERACTIONS

<table>
<thead>
<tr>
<th>Parameters Used</th>
<th>SP</th>
<th>CN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network Properties:</td>
<td>Outer point removal rate 75%</td>
<td>Idle tag beacon threshold 4 m</td>
</tr>
<tr>
<td>Average tag count</td>
<td>13</td>
<td>13.4</td>
</tr>
<tr>
<td>Average link count</td>
<td>20.5</td>
<td>29.8</td>
</tr>
<tr>
<td>% link made within project</td>
<td>30.2</td>
<td>24.2</td>
</tr>
<tr>
<td>Idle tag area threshold 2 sqm</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cluster centre distance threshold 4 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Idle tag area threshold 1 sqm</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cluster centre distance threshold 2 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Idle tag removal success rate (%)</td>
<td>84.2</td>
<td>71.0</td>
</tr>
<tr>
<td>Control tag retention rate (%)</td>
<td>64.8</td>
<td>59.8</td>
</tr>
<tr>
<td>Control link creation success rate (%)</td>
<td>63.1</td>
<td>45.1</td>
</tr>
</tbody>
</table>

TABLE IV. THE PERFORMANCE COMPARISON OF THE TWO APPROACHES IN GENERATING SOCIAL GRAPHS OF COLLABORATIVE INTERACTIONS

<table>
<thead>
<tr>
<th>Parameters Used</th>
<th>SP</th>
<th>CN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network Properties:</td>
<td>Outer point removal rate 50%</td>
<td>Idle tag beacon threshold 1 m</td>
</tr>
<tr>
<td>Average tag count</td>
<td>25</td>
<td>38.5</td>
</tr>
<tr>
<td>Average link count</td>
<td>52.5</td>
<td>136.5</td>
</tr>
<tr>
<td>% link made within project</td>
<td>44.1</td>
<td>49.6</td>
</tr>
<tr>
<td>Average connected components</td>
<td>6</td>
<td>9.5</td>
</tr>
</tbody>
</table>

TABLE V. PERFORMANCE MEANS (ALSO SEE TABLE 9) USING COMBINATIONS OF THE PROCESS VARIABLES SHOWN IN TABLE I AND II

<table>
<thead>
<tr>
<th></th>
<th>SP</th>
<th>CN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Idle tag removal success rate (%)</td>
<td>84.2</td>
<td>71.0</td>
</tr>
<tr>
<td>Control tag retention rate (%)</td>
<td>64.8</td>
<td>59.8</td>
</tr>
<tr>
<td>Control link creation success rate (%)</td>
<td>63.1</td>
<td>45.1</td>
</tr>
</tbody>
</table>

C. Overall Sensitivity Performance Based on Ground Truth

There were several control tags placed in the space during the selected hour long sample, they are coloured in magenta in Fig. 7 and Fig. 8. It is known that during this hour long sample that tags 52, 60, 62 and 64 were the set of control tags that were carried by one person (wearing tag 1, red), whereas tags 51, 53, 55, 56, 57, 58, 61, 63, 65 and 66 were idle (left in a box on a table). We will use this ground truth to evaluate the two approaches’ sensitivity in removing idle tags and picking up links between the control tags. We interpret the idle tag removal success rate as the percentage of the 10 known idle tags that were removed by the link mining process. The equivalent control tag retention rate is also calculated for 5 control tags. We interpret the control link creation success rate as the number of output links that are between two control tags over all possible (undirected) links between the detected control tags. Please note that some of the control tags may be incorrectly identified as idle tags (see control tag retention rate), those tags were not considered when determining the list of possible control tag links.

Table V presents the above three measures averaged over all given combinations of the process variables. With all three measures the perfect score is 100%. The boxplot of the three measures is presented in Fig. 9.

The SP approach performed better on all measures. Considering CN approach utilised only one reference beacon ID and none of the RSSI values, whereas the SP approach required three reference beacon data (ID and RSSI) per tag entry, the merit of using the CN approach (such as lower data storage and processing requirements, simpler data collection system) should still be considered.

VI. DISCUSSION

The SP approach performance is highly dependent on accurate position estimates. Currently literature on indoor positioning offers alternative systems and methods with trade-off in complexity and accuracy [13], [14]. Our rule-of-thumb is to select a WSN set up that gives reliable RSSI to distance relationship and/or set up a regular grid beacon configuration with unbiased tag to beacon signal paths. As the CN approach assumes interaction based on simultaneous detection at a common beacon, we would wish for the beacon-tag registrations to be more related to the targeted social behaviours. In real world applications this translates to installing beacons at representative social gathering locations, for example at a party we could put a beacon on the drinks table, one near the food, one per lounge area. If using the SP approach we would install beacons on the function room ceiling according to a regular grid. Another consideration is whether the program and the layout of the room is likely to change. For example if the workshop project groups were given more flexibility to change and negotiate space allocations, or were more mobile, then using the CN approach and having beacons installed on project specific equipment that moved with the group would be expected to perform better than the SP approach.

The spatial properties and the nature of human behaviour should be taken into consideration when selecting the process parameters. In our case study each of the design projects were given an allocated space (see Fig. 6). This gave a good indication of the spatial parameters cluster centre distance threshold. The location and placement of the beacons and
possible signal interference introduced bias into the data. Outer point removal rate and weak link removal rate were introduced to compensate for these, but we could still observe performance variation between the data collected from the top right room, the main atrium and the long open studio space.

We are currently developing a solution that combines the SP and CN approaches that utilises the better idle tag removal performance of the SP approach with the spatial context adaptability of the CN approach. The new system will incorporate flexible parameters using machine learning principles. We are also extending the evaluation of our solution to other datasets that were collected by us as well as external datasets.

VII. CONCLUSION

The aim of this study was to design an efficient process that produces reliable links to represent the interpersonal interactions occurring between the tagged workshop participants. In this paper we presented two possible approaches: the signal processing approach and the complex network approach. With each approach there are a set of variables that we can use to adapt the process for a specific interaction. Through applying these two approaches to a set of real world indoor tracking data we demonstrated the capability and adaptability of both approaches in producing meaningful social interaction graphs.

In the design workshop case study presented here, with relative open spatial plan and regular beacon layout the SP approach offered better performance. The CN approach should not be discounted as it utilises less data (one beacon sighting per tag data) and offers adaptability in more complex spatial and behaviour environments. We proposed a set of parameters for each approach that allowed the graph mining process to be fine-tuned for different scenarios. This allows our proposed approaches to be applicable to a wide range of social contexts and contribute to the discussion and development of the field of social interaction analysis.

ACKNOWLEDGMENT

The authors would like to thank the participants of the SmartGeometry2014 Workshop for their support and contribution to the case study reported in this paper; we also thank the SmartGeometry Group and the Chinese University of Hong Kong for giving us the permission to conduct data collection. We wish to acknowledge the technical contribution from Nathan Williams in the setup of the data collection system. This research was supported under Australian Research Council’s Integrating architectural, mathematical and computing knowledge to capture the dynamics of air in design funding scheme (project number DP130103228).

REFERENCES


A. Published papers

A.6. Understanding face to face interactions in a collaborative setting: Methods and applications


Abstract

Extensive studies have shown that face-to-face interactions are a critical component in a work environment. It is an effective communication method that builds trust between team members and creates social ties between colleagues to ease future collaboration. In this paper we present our interaction analysis system that utilized an indoor tracking system to provide insights on the spatial usage and interaction dynamics in collaborative spaces. This gives space layout designers and managers quick feedback on the performance of the space and its occupancies and allows interventions and evaluations to be conducted to fine-tune the space layout or organization structure to achieve optimal performance. We demonstrate our system with data collected from a recent international design workshop.
Understanding face to face interactions in a collaborative setting

Methods and Applications

Mani Williams¹, Jane Burry² and Asha Rao³

¹,²,³ RMIT University
{mani.williams,jane.burry,asha.rao}@rmit.edu.au

Abstract. Extensive studies have shown that face-to-face interactions are a critical component in a work environment. It is an effective communication method that builds trust between team members and creates social ties between colleagues to ease future collaboration. In this paper we present our interaction analysis system that utilized an indoor tracking system to provide insights on the spatial usage and interaction dynamics in collaborative spaces. This gives space layout designers and managers quick feedback on the performance of the space and its occupancies and allows interventions and evaluations to be conducted to fine-tune the space layout or organization structure to achieve optimal performance. We demonstrate our system with data collected from a recent international design workshop.

Keywords: Face-to-face collaboration, indoor tracking, social interaction analysis, team management, workspace design.

1 Introduction

In recent years we have seen a growing interest in monitoring human movement to understand social behaviors for a range of applications from context aware advertising to security and surveillance. This is pushing cutting edge research and development in the field of wireless sensor networks, data mining and visual analytics to develop more effective and efficient ways to track, model and visualize the dynamics of social interactions. For our research we are tapping into this rich multi-disciplinary knowledge to study the dynamics of social interactions that occur in a collaborative teamwork environment.

The pioneer in this field is Alex Pentland who leads the MIT’s Human Dynamics Lab. They have deployed their multimodal wearable sensor system “Sociometric Badges” to study interaction patterns in many large organizations [1]. The Sociometric Badge system extends the traditional laborious data collection techniques in studying collaborative interactions in design processes [2-3] and professional workplaces [4]. Apart from collecting longitude data for studying organizational-wide behaviors, a version of the Sociometric badge system is designed to provide real-time
feedback on the dynamics of a face-to-face interaction, such as a team meeting, to promote better team integration.

Recent findings coming out of the Human Dynamics Lab show that the pattern of social interactions, especially face-to-face interactions, is a very good indicator of the productivity and creativity of a team [1]. Extensive field studies have linked employee productivities with office layout [4]. We see this as a great opportunity for the architecture profession to join and contribute to the discussion of what the future workplace should be.

The center of the Sociometric Badge system is a multimodal data device that records the wearer’s physical movement, voice levels and proximity to others [5]. In many situations this may not be appropriate. Our work focuses on a different approach. Our system is more adaptable in terms of input source and output format. We utilized a commercially available proximity-based indoor tracking system to provide ongoing input data for analysis. The tracking data is processed to produce real-time reports on the face-to-face interaction. The analysis process and resulting visualization is supported by supplementary contextual data from the client. We believe an efficient system is one that is customizable to our client’s needs, which are expected to evolve over time.

We have compiled our research into a deployable system. We have targeted our system for two applications. The real time analysis results allow managers and project teams to monitor the development of projects as they evolve and enable them to respond to changing needs more effectively and efficiently. Our system can also be used to provide reports and feedback on the optimal office layout and the organization structures that operate within it.

In the remainder of this paper we will first introduce the methodology of our system. Next, each stage of our system will be described in detail and be supported by related work. The capability of our system for real world application is demonstrated with a case study. The paper will conclude with a discussion of its two suggested applications and recommendations for implementation in other contexts.
2 Methodology

2.1 Data collection

Adaptation of face-to-face interactions research into industry practice is lagging behind the acceptance of Big Data and virtual communication mining due to the hurdle of deploying a data collection system. Established methods of collecting face-to-face interaction data such as questionnaires, surveys or direct observations are resource intensive, subjective and thus hard to integrate into the everyday management decision-making process or design process.

We are interested in tracking human interactions during the subjects’ normal work environment. Tracking data can be in the form of position tracking that records the trajectory of people as they move around, proximity tracking that records the distance between people and/or a person and surroundings [6], or association logging that detects interaction events based on multiple input criteria [5,7]. Lui [8] and Gu [9] surveyed tracking methods and applications. Current wireless sensor networks (WSN) development have achieved indoor positioning accuracy of less than a meter [10].

A suitable data collection system should be automated and non-intrusive. Automation reduces repetitive manual labor and enables a continuous data stream to be available for live analysis and decision-making. We advocate ethical care towards our study participants that ensures participation is voluntary and consensual. A non-intrusive set up, such as a wearable tracking tag that can be removed, allows our participants to have control of their privacy.

When possible, supplementary data should also be collected. These include floor plans, organizational diagram, project description and schedule, as well as automated
contextual data such as ambient sound level and other environmental conditions. This information helps us to contextualize and evaluate our analysis.

2.2 Behavior modeling

For us to get meaningful results, we need to build a behavior model that describes the scenarios that we wish to observe. A behavior model needs to be defined and constructed from the collected tracking data, supplemented by the context data. This is one of the opportunities for us to guide the analysis system to be specific on what it is that we are interested in.

Regarding proximity in face-to-face interactions, the classic proxemics theory of Edward T. Hall [11] categorized the four types of interactions (intimate, personal, social-consultive and public) by person-to-person proximity. Waber [12] used spatial constraints such as desk, corridor, floor and building separations to categorize interaction distances. Research in office layout found that both the frequency and the duration of interactions are correlated with employee performance [13]. Frequency and duration can be combined to produce a complex proximity measure [14].

We propose to divide behavior modeling into two components. Firstly filter the input data stream to remove irrelevant data. For example if we wish to study evolution of collaboration dynamics within project teams, we would need to process the data to identify events of collaboration and the participants that were involved in those events. Let us suppose that the organization that we are studying supplied us with a list of participants that belonged to a particular project. Through proximity tracking we can identify when the project members met and for how long. If we know the locations of the meetings through position tracking or environmental proximity tracking, or we have access to the project schedules, we can isolate the meetings that were project related.

Once we have a list of individuals and a list of events that link subsets of the individuals together, we can construct an interaction network that represents the behavior model that is specific to our query. We can also introduce dynamics into the network by adding the time variable. With the interaction network at hand we are now set to apply a large array of complex network based analysis and visualization to extract meaning from our behavior model.

2.3 Analysis

Complex Network Analysis (CNA) is a multidisciplinary field of research that investigates relations (network links) between a set of individual identities (network nodes) that are representations of real world phenomena, ranging from human biology to the World Wide Web. Supported by rapid growth in computing power, data collection and storage capacity, CNA is a relatively active area with contributions, both from and to, computer science, mathematics, sociology, and biology to name a few. By constructing our behavior model as a complex network we can apply CNA methods to examine the behavior at multiple levels. We can compare behaviors of individuals by observing their position and importance within the network; group
certain individuals together based on contextual attributes and observe interaction within and between the groups; and observe interactions between individuals at the organizational level to get an overview of the underlying structure of the behavior.

Social network centrality measures such as degree, closeness and betweenness [15] are network analysis methods that calculate the importance of a network node within the network. They are calculated based on the number of links a node has (degree), how easily a node can reach the rest of the nodes in the network (closeness) and how critical a node is to the structure of the network (betweenness). Translated to our context an individual with a high degree measure indicates he/she was quite active, since that individual had lots of interactions with a range of people. Looking at the closeness measure allows us to pick out the more integrated individuals; they may not have met with the most people but they tend to have the best idea of how everyone is going, since news (or gossip) travels through fewer paths to reach them. If you want to know the employee you shouldn’t lose, then the betweenness measure would be a good indicator: a person with a high betweenness measure indicates that he or she is the critical node between two sections of the network, if you take him or her out part of the organization may fall apart unless new links are made elsewhere.

In the context of face-to-face interactions in a collaborative work environment we are working with what is called “Small-world networks”, where the people an individual interacts with are mostly likely to also be interacting themselves, or “friends of friends are also friends” [14], [16]. This node level or network level property is call clustering or transitivity [17]. Within a project group an even transitivity means that there was a healthy communication flow between the group members. Another network property of interest is cohesion [18]. Similar to the betweenness centrality measure, cohesion represents how many nodes need to be removed to disconnect the network, and hence it observes how close knit a group is. Studies have shown that at different stages of the creative process different interaction network structure (represented by its cohesiveness) should be encouraged: A star-like diverse network is suitable at the conceptual discovery stage where the project is collecting ideas; a cohesive network is good for the development stage where everyone works together towards the final goal [12]. Both transitivity and cohesion are applicable at a group level as well as the overall organizational level.

Another aspect of group behavior worth investigating, especially in the architectural and design context, is the spatial preference of behaviors. This builds on the proximity analysis component of the behavior modeling stage where we utilized distance dependent proximity readings to generate interaction links. This is best represented graphically, overlaid on a floor plan, to demonstrate the relationship between individual/group/overall activity intensity and space usage.

As behavior is highly dependent on the context, we recommend a more qualitative approach to representing analysis results. Through network visualizations we can compare the change in the behavior pattern across time samples and groups. Supplementary data such as project roles and team assignment can also be included in the graphical composition of the visualizations to introduce contextual information to assist with result comprehension.
In the remainder of the paper we will demonstrate a combination of the introduced method with a set of real world data collected by the author.

3 Case study

We have collected data from a recent international design workshop attended by students and professionals from the design industry, based on a collaborative teamwork framework where the attendees formed several project teams. The collaborative workshop event aimed to encourage positive interaction within the teams to work towards a common project outcome, stimulate interactions between teams to exchange ideas and skills as well as foster new social, professional and academic connections. Over the course of four days, we have tracked the movement of more than fifty participants using an indoor tracking system.

A set of supplementary data was also collected:
- The development of the project teams was documented through a set of time-lapse cameras.
- Field notes recorded through participant observation by two of the Authors.
- From the workshop organizer we obtained a floor plan with the project activity allocations’ noted (Fig. 2).
- From the individuals that agreed to participate in the tracking exercise we collected their name and project assignment.
- Publically available information collected were:
  - Workshop schedule, project descriptions, proposed project schedules and names of the project leaders and participants.
Fig. 2. Case study: the floor plan of the workshop. Main activity spaces are marked. Twenty-two tracking beacons (blue dots) were installed near to the activity spaces, and where possible, placed in a relatively regular fashion. There were a total of eleven project groups participating in this workshop, out of which tracking data from eight of the project groups were analyzed for this paper.

3.1 Data collection and preparation

The data collection occurred over four days of the workshop event that included: three days of workshop days, one final day of daytime offsite presentation and an evening exhibition onsite. During the workshop days the participants had access to the space from approximately 8 am to midnight.

The tracking data collection was conducted using an off-the-shelf ZigBee-based indoor tracking system, which periodically output proximities of wearable tags to several static tracking beacons. This allowed us to estimate the position of people in a preset space when the tags were carried: the tag position estimates were calculated as the mean X, Y coordinates of the detected beacons’ coordinates, weighted with the corresponding beacon RSSI readings. A log of the position was recorded in a database for further analysis.

Fig. 3. Tracking data showing spatial usage of the eight represented project groups.

3.2 Behavior modeling

We constructed our behavior model based on the tracking tag positions. Data was grouped into 10-minute data samples. Statistical analysis was applied to calculate an activity center and an active area for each of the tags that were present during the data sample. A tag area threshold, determined from experimentation, was applied to
remove idle tags. These tags were most likely left on the table or in the person’s bag thus did not represent the behavior of the person it was assigned to.

Proximity analysis was applied to all of the remaining active tags:

1. Distance was calculated between all of the active tags detected in the same data sample. This generated a list of proximities between active tag pairs.

2. Referring to the tagged person’s project assignment, we categorized the proximity list into in-group proximity and out-group proximity.

3. The out-group proximity threshold of 3-meters was applied to extract a list of out-group interaction tag pairs. The 3-meters threshold was determined from onsite observation and in consideration of Edward Hall’s 10 feet personal-social proxemics threshold [11].

4. As the activity of each of the projects differed, ranging from computer-based work to large physical prototype construction, an adaptive in-group proximity threshold was required. Through experimentation, we found that the mean distance values achieved a good balance between removing tag pairs that were too distant to be effectively communicating face-to-face and preserving sufficient activity tag links to model in-group behavior.

The interaction network was constructed from a subset of the proximity list, characterized by a time range and/or the participants in the interactions:

• The interaction network node represents the list of active tags present during the proximity list. The node attributes were: tagged individual’s project allocation and role, the list and count of the activity center coordinates that the tag was calculated to have visited and the activity centers’ corresponding active area size.

• The interaction network links represent the pairs of activity tag nodes from the proximity list. The link attributes were: in-group/out-group categorization, the coordinates of the link (taken as the mid-point between the connected two tag coordinates).
Fig. 4. Demonstrating the adaptive in-group proximity thresholds (marked). The line plots represent the density distribution of the in-group proximity pair for each of the eight project groups. The color-shaded backgrounds represent all of the out-group proximity pairs that the project group participated in. The gray background represents the distribution of all of the calculated proximity pairs. Looking at the in-group proximity lines, we can see that the RN and DS groups have sharp narrow peaks close to the origin, this tells us these groups were physically static. This agrees with the onsite observation: RN and DS were computer-based design projects. Also observe the SG in-group proximity line has two peaks, this indicates the SG group had two modes of operation: our field notes confirms that during this data sample period a select members of the group were tasked to man the project table and others left to visit other projects. Comparing the color-shaded out-group proximity with the workshop result in gray, focusing on the region near the group mean threshold, tells us the amount of distraction the group experienced and produced. For example for FBR its out-group proximity distribution closely matched with its in-group distribution, translates to that for FBR members within their work radius it is nearly as likely to encounter someone from a different project than one from their own.
This is the interaction network that models the behavior of the workshop compiled over the whole data collection period. The network layout was optimized using the force-directed Large Graph Layout algorithm [19-20]. The nodes were colored by their project allocation, and the shape indicates the individuals’ roles: square representing the project leaders and circles representing the participants. As expected the interaction network visualization showed a clustering behavior that coincided with the individuals’ project allocation. The variance between the project groups suggests difference in work patterns, for example the light green (RS), yellow (RN) and orange (SE) project group members appeared to have mingled more with each other.

3.3 Analysis and visualizations

The force-directed network layout (demonstrated in Fig. 5) gives us a good visual overview of the strategic importance of each individual’s contribution to the overall workshop interactions. We can highlight different behaviors by applying the three aforementioned social network centrality measures to the interaction network. Fig. 6 demonstrates the behaviors of individuals in the workshop during an afternoon.
A cohesive group interaction network represents a healthy collaborative teamwork. This is best represented graphically by constructing an in-group interaction network for each of the project group by extracting the network links that connects the nodes belonging to the same group. A circular node layout was used, as it is best for presenting the interaction patterns. The node shape identifies project roles; node size represents the number of interactions that individual had participated in. A fully cohesive network is one where balanced network links exist between all of its team members, and is more common in a facilitated meeting; for project work a biased interaction network was expected, as the ones shown in Fig. 7. Our field notes and supplementary data confirmed that during the represented time sample, there were distributions of the tasks to form sub-groups within projects.

In a collaborative co-located work environment, such as the one from the case study workshop, the amount and diversity of out-group activity can be both a blessing and a curse: too much interaction between different groups distracts the team from working on its own projects, but not enough out-group interaction most likely shows that the project has not explored the skillsets and expertise from people outside the project. As seen in Fig. 8, with reference to the floor plan in Fig. 2, project PM was more isolated and had limited interactions with other projects. Interestingly both the ST (teal) and SG (purple) teams were relatively centrally located but their members did not interact much with other project teams either.

It is worth investigating when a project team was shown to be involved in a large amount of out-group interactions, identifying with whom (Fig. 9) and where those interactions occurred (Fig. 10), and if more contextual information is available, to check whether the interactions level was a distraction to the teams involved. In the case of the neighboring projects SE and RN the interaction was disruptive and a few screens were requested to construct a barrier between the two project spaces.

Interaction dynamics are difficult to quantify and measure. Presenting the organization-wide analysis result alongside results from individual groups (such as Fig. 8 and Fig. 10) helps the viewer to understand the variation and cause of the interactions. Organization wide dynamics can also be perceived through comparing visualization across time sample. To this end, we divided the data into timed sample blocks: each day’s data was separated into morning (8 am to 1 pm), afternoon (1 pm to 6 pm) and evening (6pm to 8am of the next day), resulting in twelve sample blocks. We then constructed an interaction network for each of the sample blocks and generated the organization interaction diagram based on the degree centrality measure (Fig. 11) and the interaction spatial map (Fig. 12).
Fig. 6. Organization interaction diagrams as recorded during the afternoon session of day 2 of the workshop, using the degree (left), closeness (middle) and betweenness (right) measures represented as node sizes. These respectively corresponded to emphasis on the individuals’ activeness, integration and criticalness, with the node size representing the measure value, and the color indicating the individual’s project allocation.
Fig. 7. In-group behaviors of the eight project groups as recorded during the afternoon session of the day 2 of the workshop. The node shape indicates the individuals’ role: square represented the project leaders and circles represented the participants. From the variations in the weight of the interactions between project group members we can observe sub groups have formed in the projects.

Fig. 8. Ratio between in-group interactions and out-group interactions compared across the eight project groups. Due to its spatial isolation (as seen in Fig. 3), project PM (red) had limited interactions with other projects. Interestingly the SG and ST teams were relatively centrally located but its members did not interact much with other project teams.
Fig. 9. Out-group behaviors of each of the project groups, the interaction participants are highlighted in the organization interaction diagram. Interesting observation comparing SG and FBR projects: although SG team had conducted more in-group interactions during this workshop session, it has met up with a large proportion of the workshop participants; whereas FBR group member’s out-group interactions were less frequent and more selective.

Fig. 10. Interaction spatial maps, top: Locations of where the project groups engaged in in-group interactions (colored) and out-group interactions (gray); bottom: The group data is combined to produce the spatial interaction map for the organization.
Fig. 11. The organizational-wide interaction diagrams, individual level interaction intensity are emphasized by the size of the individual nodes (degree centrality). Day 1 to 3 were workshop days, day 4 was the final day consisting of a daytime offsite presentation and evening onsite exhibition. Node color represents project associations. As we can see from the twelve sequential diagrams, as expected, the interactions that occurred showed high project clustering preference, but of more interest to us is that through these diagrams we can also observe variations between the sample time periods: The interactions became more project orientated as time progressed towards the conclusions of the workshop (on day 3), this is vastly different from the interactions that occurred during the exhibition (evening of day 4) when people mingled while visiting each other’s project exhibit.
Fig. 12. The organization-wide spatial interaction maps showing the locations of in-group interactions (colored pink) and out-group interactions (black), as recorded by the four days of tracking data. Presented spatially and sequentially we can clearly observe the change in the spatial usage of the workshop as the workshop progressed. The increase in in-group interaction intensity observed from the interaction diagram shown in Fig. 11 can also be seen here: The color intensity in the day 3 diagrams is more evenly distributed compared with days 1 and 2.

3.4 Interpretation

As mentioned above, goals of the outcome of the workshop are to provide an environment for attendees to participate in one of the allocated projects, as well as to stimulate idea exchange and foster new personal connections between the attendees. For many people this was a constant balancing act, “I really wanted to see the other projects, but I needed to get this done first.” Project PM (colored red) had requested an isolated space to provide a stable test environment for its experiments. From Fig. 11 we could see the impact of this spatial segmentation had on the workshop-wide interaction network: the PM members had formed a close-knit cluster with little interactions with others. Some relief from this isolation can be seen on the afternoons of day 1 and day 2, when the workshop had organized presentations attended by everyone, although it is clear that this temporal integration had little long-term impact. From this we can conclude that spatial segmentation should be avoided in future workshops, in cases where a controlled environment is required, temporal partition is preferable to permanent separation of project spaces.
Too much spatial overlap can also introduce issues. Project SE (orange) was assigned two spaces, one in the building atrium, one in the bottom left end of the long open studio space. This meant there was regular traffic between these two spaces, directly impacting the operation of the RN (yellow) group. Before long, two movable screens were put in place to provide partition between RN’s space and SE’s space. In this case, the Fig. 10 spatial heat maps clearly demonstrate the disadvantaged situation of the RN project: they have the smallest in-group heat map because their in-group interaction was over flooded by the distractions from their neighbors. This could also be seen from the Fig. 4 proximity distribution. The RN group had the narrower in-group proximity plot; this indicates that the RN had positioned themselves physically close to each other, most likely to stay away from the foot traffic. In comparison, project FBR (purple) was also centrally located with possible distractions coming from three sides, but as seen in Fig. 10, they managed more undistracted in-group interactions. This was because the FBR was allocated a wide space, which acted as buffer to protect the project from unintentional distractions. Based on these observations and interpretations, we recommend that future workshop space allocation consider traffic distractions around projects and allocate additional buffer spaces to projects that may be affected.

Looking across the time samples (Fig. 11 and Fig. 12), we could detect the increase in the preference of in-group interactions throughout the workshop as the projects progressed closer to completion (end of day 3). The organization-wide interaction diagram (Fig. 11) became more clustered according to project colors, and the spatial map (Fig. 12) became more saturated with in-group interactions. This is an accurate indication of the status of the healthy project progress.

4 Applications

We have presented a proximity-based interaction analysis system to give us insights into many aspects of the collaborative environment. In this section, we will demonstrate how our methods can be used for other real world applications.

4.1 Office Spaces

Office spaces have shifted from individual cell based configuration towards a flexible open-plan with mixed-use zoning configuration. Driven by commercial incentives [4], and supported by research suggesting that an increase in informal interactions between employees have positive contribution to productivity [1], [12-13], this trend is sure to continue.

Although the literature still debates the quantity and quality of interaction that achieves best workplace performance, extensive research supports the proposition that the geometrical layout influences human behavior and communication patterns between individuals [13].

Existing organization-planning studies are still heavily dependent on a questionnaire approach to collect interaction data. Questionnaires are known to be
subjective and have a low response rate. In comparison, our wearable sensors data collector is non-intrusive and is capable of providing automatic and objective interactive data. Our analysis system can then generate live reports on the current interaction patterns in the workplace. For optimal organization performance, interaction patterns should match the organization structure and task dependencies. Our reports (Fig. 7-11) allow organizers to identify and encourage positive interactions as well as implement early intervention to remove distractions.

Ongoing spatial usage evaluation is required to ensure the compatibility between the spatial layout and the intended interactions. Current space auditing processes are still manual observation based, requiring timed visits to each of the designated spaces to conduct head counts. Our interaction analysis system can automatically produce historic reports of the space usage (Fig. 10 and Fig. 12). This information is valuable for the active management of workplaces [4]. For example, the outcomes from the interaction analysis can be used to flag spaces that require activation and recommend reconfiguration of employee desk allocation.

4.2 Project Management

A project team can use the in-group interaction diagram (Fig. 7) to manage the communications in the team. The team members can become more aware of the dynamic of the in-group interactions through monitoring the real-time report of the in-group interactions. This should encourage a more balanced contribution of the team members, build trust and integration within the team and contribute to better overall performance. The out-group interaction diagram (Fig. 9) is useful for identifying expertise from the organization to be included in the project.

On a higher level, company management can also gain insights from interaction analysis. From the individual level analysis such as degree and betweenness centrality measures (Fig. 6) we can discover persons and relationships that may require additional support or to be encouraged through reward. A combination of face-to-face in-group engagement and out-group exploration is indicative of the creativity and productivity level of a project team [1]. Although the context of each project can be unique, the availability of live and historic interaction data allows the managers to have close engagement with the teams to find the winning formula for best performance.

4.3 Remark

It is important to refer to other contextual information before making any judgment on the performance of the individual or a group. Each scenario is unique, and how people interact also changes with time. When possible, multiple data sources should be tracked and fed into the behavior model. The face-to-face interaction analysis methods presented in this paper can be easily adapted to be applied to other interaction data sources, such as email communications, social media engagement and other virtual interactions. Those data sources can be combined with tracking data through additional proximity analysis methods, such as multi-criteria threshold, or be
processed independently and combined with tracking data results at the visualization stage through the use of graphical annotations or overlays.

5 Conclusion

In this paper we presented our development of a face-to-face interaction analysis system that is targeted for use in collaborative work environments to generate insights on how people interact with each other.

We have demonstrated the capability of our system using the data recorded at a recent international design workshop. By focusing on visual presentations our analysis methods were able to uncover insightful engagement patterns that informed us of a range of dynamic behaviors including participant engagements, project group collaboration and overall workshop dynamic. In specific to this case study, our analysis was able to identify scenarios of interest and provide recommendations for the planning of future events.

The system and methods presented here have applications in increasing the program compatibility of office layout designs, supporting an active workspace management for efficient facility usage, as well as improving team performance at both an individual and a management level.

Our research contributes to the advancement in the field of architecture and computation by connecting our profession with the cutting-edge development in social mining and people analytics, thus preparing us to actively engage with the changing social context that is surely to come with “the next city”.

Acknowledgements. The authors would like to thanks the organizers of the SmartGeometry 2014 Hong Kong workshop and its host Chinese University of Hong Kong for allowing us to conduct data collection. We also acknowledge the participants of our case studies. This research was supported under Australian Research Council’s Integrating architectural, mathematical and computing knowledge to capture the dynamics of air in design funding scheme (project number DP130103228).

References

B. Unpublished Writings

B.1. Visualizing Dynamic Bipartite Network with Spatial Attributes: a Force-Directed Approach

Abstract

We propose a novel bipartite network visualization approach that takes advantage of the bipartite nature of a spatial interaction network to incorporate spatial attributes into the network visualizations. The iterative nature of a force-direct approach lends itself to be applied to static as well as dynamic networks. This approach is not only suitable for visualizing the dynamic network behavior directly, but also to support the display of additional network analysis results. The outcomes of the presented method could be incorporated into other forms of data analysis and visualizations. We will demonstrate the features and potentials of this approach with a spatial interaction dataset collected by the author.
Visualizing Dynamic Bipartite Network with Spatial Attributes: a Force-Directed Approach

Abstract—We propose a novel bipartite network visualization approach that takes advantage of the bipartite nature of a spatial interaction network to incorporate spatial attributes into the network visualizations. The iterative nature of a force-direct approach lends itself to be applied to static as well as dynamic networks. This approach is not only suitable for visualizing the dynamic network behavior directly, but also to support the display of additional network analysis results. The outcomes of the presented method could be incorporated into other forms of data analysis and visualizations. We will demonstrate the features and potentials of this approach with a spatial interaction dataset collected by the author.

I. INTRODUCTION

Network theory is a branch of graph theory that studies the relations (known as links or edges) between discrete objects (nodes or vertices). This approach has been adopted by disciplines such as social science, health science and information technology to model and analyze complex phenomena. Advances in technology enable us to capture and analyze large quantities of network data, many of which are dynamic in nature, which represent the evolution of the phenomena under study. Researchers in data visualization and visual analytics are working on methodologies and guidelines to assist other researchers to effectively comprehend and communicate their findings on the applications of dynamic networks. Withall et al. [1] give guidelines on the visualization of communication networks, where as Lodde [2] give guidelines on information networks. The design guidelines presented by Kornhauser et al. [3] on the visualization of agent-based modeling can be applied to the designing of network visualization. Abello et al. [4] explore the options to reveal local and small dynamic changes in the large datasets through identifier tracking. Van den Elzen et al. [5] propose a graph optimization approach to highlight network structure. Nesbitt and Friedrich [6] and Bach et al. [7] both proposed animated transitions to assist the visual perception of a dynamic network.

Current work in network visualization has focused on 1-mode networks where the algorithm assumes links are possible between any object pairs. Many real-world networks are in fact studies of the interactions between two independent classes of objects, where links only exist between objects of different classes. This is known as a 2-mode or bipartite network (Borgatti and Everett [8], Latapy et al. [9]). There are two approaches to the analysis and visualization of bipartite networks: the unimode approach and the bimode approach (Borgatti [10]). With the unimode approach the network is transformed into a 1-mode network through projection, and further standard 1-mode network analysis can then be applied. The disadvantage of this approach is that with the removal of one set of nodes from the network the information contained in those nodes can only be represented through additional link attributes such as a weighting or labeling.

The bimode approach retains the bipartite information and treats the two node sets as independent node groups. Analysis is conducted on both groups simultaneously but normalized within the respective group before being brought back to the network level. When visualized the two node groups are distinguished graphically, and placement of the nodes are either optimized to display network structure or mode-mode interaction. Note that with the standard bimode approach identical layout placement calculation is applied to both sets of the nodes, either together or independently. This ignores the possibility of characteristic differences between the two modes.

More often data from these networks have a spatial attribute attached to them, such as GPS coordinates or received signal strength indication recorded by a mobile device. Although these spatial attributes could be precise or relative, they should help with the comprehension of the overall network data by anchoring the abstract, sometimes overwhelming, network visualizations back into the reality. This is the intuition behind the work presented here.

The two node groups of a bipartite network can be distinguished as primary and secondary nodes, where the primary node set is considered responsible for link creation [11]. This is the basis of our alternative bipartite network visualization. Through visual cues we aim to reveal the underlying dynamic of a bipartite network by emphasizing the effect of the primary node on the network links. Physics system based layout algorithms such as a force-direct layout are perfect for providing these visual cues. The iterative nature of the force-directed layout algorithm also has the added benefit that it can be easily extended into an efficient and effective visualization algorithm for dynamic networks. We will demonstrate this with a set of real world spatial interaction network data collected by the author.

II. THEORETICAL DEVELOPMENT

Force directed layout (FDL), such as the Fruchterman and Reingold layout [12], is a type of graph drawing algorithm that generates network diagrams by the use of attraction and repulsion calculations to place nodes for better visual perception of the network. FDL presents the network as a physical system where the attractive and repulsive forces are calculated along the links between nodes and theoretically optimal layouts are achieved when the physical system is at equilibrium; in practice an estimate is calculated through an iterative process. Initially the nodes are placed either at predetermined locations or placed at random. With each iteration the nodes, similar to physical objects, are allowed to move closer to or further
away from each other determined by a set of attraction and repulsion forces. This repeats for many (fixed) iterations, the final placement being an acceptable approximation to the optimal placement.

There are different presentations and variations of FDL; each developed for a combination of performance considerations such as calculation efficiency and visual aesthetics. Based on the Fruchterman and Reingold layout, Bannister et al [13] introduced additional calculations to optimize the FDL to better reflect the centrality characteristic of the nodes. We have selected this version of the FDL to develop further as it is an effective algorithm that allows different distance dependent attraction and repulsion effects to be applied to the nodes.

A. Adaptation to bipartite data

To adapt FDL to a bipartite graph $G = (V_p, V_s, E)$ we will make the following adjustments regarding the treatment of the nodes.

- When deciding which bipartite node sets to take as the primary node set, we select the node set that has known spatial attributes.
- Known spatial attributes are incorporated into the positions of the primary nodes and are kept stationary. Position updates are only calculated for the secondary nodes. This allows the visualization to emphasize the effect of the primary nodes $V_p$ on the secondary nodes $V_s$.
- The spatial context can also be incorporated into the initial positions of the secondary nodes.
- We assume that the primary nodes are responsible for the creation of the bipartite links $E$. Attractive forces are not calculated between secondary nodes. Repulsive forces are calculated based on all nodes.
- As attraction and repulsion represent different behavior, we introduce separate attraction factor $\alpha$ and repulsion factor $\rho$ to independently control the effect of the attractive and repulsive forces.

For a bipartite graph the equations (Eq. 1-4) below are used to iteratively calculate the node placement for a secondary node $n \in V_s$. $d$ represents the distance between two nodes, $f_a$ and $f_r$ represent the attractive and repulsive forces respectively, $n_{\text{displacement}}$ represents the incremental change in position, this updates $n_{\text{position}}$, the position of the node $n$. The pseudo code is presented in Table I.

$$f_a(d) = \alpha d^2$$  \hspace{1cm} (1)
$$f_r(d) = -\rho d$$  \hspace{1cm} (2)
$$n_{\text{displacement}} = \sum f_a + \sum f_r$$  \hspace{1cm} (3)
$$n_{\text{position}}(i) = n_{\text{position}}(i-1) + n_{\text{displacement}}$$  \hspace{1cm} (4)

Although the parameters are network specific and best found experimentally, we provide the following guidelines:

- Attractive force $f_a$ is the main contributor in determining the final placement of the nodes. The attraction factor $\alpha$ should be determined in consideration of the area of the placement plot and the number of iterations.

$$\alpha \sim \frac{1}{\sqrt{A_{\text{plot}} \times \#\text{iterations}}}$$

- Repulsion factor $\rho$ should be determined in consideration of a repulsion radius $R$ (see below), spatial scale of the network (or the square root of the plot area) and number of nodes.

$$\rho \sim \frac{R \sqrt{A_{\text{plot}}}}{\#\text{nodes}}$$

- When possible the repulsion radius $R$ should reflect the context of the network data. For example if the network represents a set of human interactions within a room, then $R$ may be the radius of the human to human physical space.

$$R \sim \text{expected min} \vert n_{\text{position}} - n_{\text{position}}' \vert$$

- If context information is unknown or is not required to be considered, $R$ should be approximated by:

$$R \sim \sqrt{\frac{A_{\text{plot}}}{\#\text{nodes}}}$$

which gives:

$$\rho \sim \frac{A_{\text{plot}}}{\#\text{nodes} \sqrt{\#\text{nodes}}}$$

- We found 50 to 100 iterations can achieve good node placement when examined visually.

B. Static to dynamic network

Collecting two-mode data over multiple time periods produces a dynamic bipartite network. By studying the change in the network structure between time samples we can analyze the time dependent influence of the nodes on the network.

Let us consider a basic un-weighted bipartite dynamic network $G = (V_p, V_s, E, T)$. With each time sample $t \in T$, we will collect two-mode data $m_t$ and $n_t$ at each time sample $t$. For time dependent analysis, we introduce the following calculations: Computation of the node positions.

<table>
<thead>
<tr>
<th>Table I. Pseudo code for the adapted FDL</th>
</tr>
</thead>
<tbody>
<tr>
<td>for i in 1 to iterations do</td>
</tr>
<tr>
<td>for each secondary node n in the network do</td>
</tr>
<tr>
<td>calculate attractive force from linked primary nodes p</td>
</tr>
<tr>
<td>$F_a = \sum_{(p, n) \in E} f_a(p, n)$</td>
</tr>
<tr>
<td>calculate repulsive force from all primary nodes p</td>
</tr>
<tr>
<td>$F_r = \sum_{n \in V_s} \sum_{(p, n) \in E} f_r(p, n)$</td>
</tr>
<tr>
<td>$\text{position update}$</td>
</tr>
<tr>
<td>$n_{\text{displacement}} = F_a + F_r$</td>
</tr>
<tr>
<td>$n_{\text{position}} = n_{\text{position}} + n_{\text{displacement}}$</td>
</tr>
<tr>
<td>end</td>
</tr>
<tr>
<td>end</td>
</tr>
<tr>
<td>$\text{where}$</td>
</tr>
<tr>
<td>$d(m, n)$ = $|\text{m.position} - \text{n.position}|$</td>
</tr>
<tr>
<td>$v(m, n)$ = $\text{m.position} - \text{n.position}$</td>
</tr>
<tr>
<td>$\text{attractive force from m acting on n}$</td>
</tr>
<tr>
<td>$f_a(m, n) = \alpha \times \frac{v(m, n)^2}{d(m, n)}$</td>
</tr>
<tr>
<td>$\text{repulsive force from m acting on n}$</td>
</tr>
<tr>
<td>$f_r(m, n) = -\rho \times \frac{v(m, n)}{d(m, n)}$</td>
</tr>
</tbody>
</table>
links $E(t)$ exist between a subset of the primary $V_p(t)$ and secondary nodes $V_s(t)$, which are used to generate the network $G(t)$ for this time sample.

Standard FDL algorithms default to a predetermined (random or fixed) initial node placement. By taking into account the previous time sample’s placement results, our adapted FDL is easily extended to visualize a dynamic network:

1) When present, the primary nodes take on the fixed known positions corresponding to their spatial attributes.
2) Each of the present secondary nodes are initialized with their last known location before being iteratively updated by the adapted FDL.
3) The change in the subset of the linked primary node drives the movement of the secondary nodes between time samples.

III. CASE STUDY: SPATIAL INTERACTION DATASET

There has been a growing interest in research to understand how people interact in the indoor environment. This has applications in organizational planning and workplace design. An opportunity was presented to us to monitor the behavior of design students participating in an intensive design workshop. The workshop organizers were interested in understanding utilization of the spatial set up as well as evaluating the social interactions between the workshop participants.

We were able to install proximity sensors at 9 work areas and distribute tracking tags to 14 workshop participants. The data collection system was set up such that when a tag was detected within the range of a proximity sensor a record of [time stamp, proximity sensor ID, tag ID] was automatically logged into a database. Post processing to remove noise (with a 60 second moving filter) and segment the data into 10 minute time samples resulted in 276 non-empty bipartite network datasets.

We wish to focus our analysis on the evolution of the social network formed by participants meeting other participants at the provided work areas. To achieve this we select the work areas (proximity sensors) as the primary nodes and the workshop participants (tags) as the secondary nodes. The locations of the proximity sensors were noted and the coordinates used as the spatial attributes to anchor the primary nodes, the secondary nodes were allowed to move as modeled by the adapted FDL. The visualizations are focused on conveying the dynamic nature of the network through the movements of the secondary nodes. For the rest of the paper, unless otherwise specified, we imply that the visualizations refer to the secondary nodes only.

A visualization example taken from 3 consecutive time samples is presented in Fig. 1: the network view (left) plots the final node placements with connecting links. The transition view (right) plots the intermediate calculations of the 50 iterations.

We can observe that the adapted FDL with transition view is effective in modeling the movement behavior of the participants during each time sample. Considering the number of time samples in this network, the dynamic nature of the overall network is best viewed as an animated movie using the transition view of the time samples. An example can be found on the author’s website.

As the color assignments reflect the project assignment of the participants, overlaying the time sample’s final placement
gives us a good indication of the preferred work areas of the three group projects. We can observe from Fig. 2 that project 1 (green) occupied the top left section of the room, project 2 (blue) worked mainly in the center tables and project 3 (red) favored the bottom right section of the room. (Yellow is assigned to the workshop coordinator who was present in the workshop space only a few hours a day.) Facilities offered at each of the work areas were very similar, and the participants were not assigned fixed seating. We could see that the three projects each had areas that they occupy and there are areas in this space that appear to be popular for all. To understand this further we draw on additional network analysis measures.

IV. VISUALIZATION SUPPORT FOR ADDITIONAL ANALYSIS MEASURES

Projecting the bipartite participant-spatial interaction network into a 1-mode network of interaction between participants allowed the standard social network centrality measure (Freeman [14]) to be applied to analyze the individuals connectivity to the social network within the workshop participants. We propose the following interpretations of a selection of relevant centrality measures:

- **Degree** is the number of links connecting a node to the network. As it is calculated on the immediate network, it is a measure of the direct interactions a person had. For example a person with a low degree measure indicates this person worked more independently, whereas a person with high degree measure interacted more with the rest of the group.

- **Closeness** is the inverse of the total number of links required to reach all nodes in the network. This makes closeness a representation of the central-ness of a person. A person with high closeness measure indicates that this person is more connected with the network thus more likely to have a better knowledge of the status of the workshop.

- **Betweenness** is a measure of the criticalness of one node to the overall reach-ability of the network, a bridge between two otherwise separate groups. In our workshop context a person with high betweenness measure would indicate that this person performed more of the role of a messenger.

By plotting the centrality measures using the placement derived from the adapted FDL, we can visualize the social interactions of the workshop participants in the context of the spatial arrangement of the workshop.

Here we present two alternative visualization strategies to present the centrality measures. The first is combining all three of the degree, closeness and betweenness measures together in one connectivity view (Fig. 3). Symbols are selected to mimic a person for easier interpretation, with the "head" representing the degree, the "body" representing closeness and the "diamond" representing the betweenness measure of the individual participant. Compared with the network view (Fig. 3, left) the connectivity view (Fig. 3, right) is better at identifying the differences in network connectivity between the individual nodes. This is best used to produce snapshots of the network behavior with the individual time sample network data. The sequence of snapshots can then be transformed into an animation. This animation of the connectivity view snapshots, together with the animated network view and animated transition view are all available on the author’s website.

Representing the measures separately using the overlay method, the project specific color coding allows us to perceive each project as an identity and focus on the distinct project behavior in the spatial context. (Fig. 4) We can see that
Fig. 3. Comparing the network view (left) with the connectivity visualization (right). As the secondary nodes correspond to people, we coded the connectivity visualization to mimic a person for easier interpretation: for each node the size of the "head" represents the degree, the "body" size represents closeness and the "diamond" size represents the betweenness centrality measures. This allows us to present three measures simultaneously and allows the viewer to perceive the complexity and dynamics of the roles individuals play in the overall network.

the overall degree distribution is similar to the closeness distribution. This is due to the "thinness" of the network constructed from each time sample - the links between nodes are sparse and rarely a node is linked to multiple nodes that are not already linked. This means that in any 10 minute time sample the participants have a tendency to stay with the same group of people (the groups are not necessarily formed by people within the same project). In this case the adapted FDL visualization of the betweenness measure is of most interest: when the participants do interact between groups, where does it occur? Compared with projects 2 and 3, project 1 has a scattered distribution of the intergroup interactions, occurring not only in its home base (as perceived from Fig. 2) but also into the preferred work area of the other projects.

Each set of centrality measures can also be interpolated over the complete area of the workshop space to produce a heat map representation of the degree, closeness and betweenness distributions (Fig. 5). Interpolation produces a more direct spatial perception of the distribution and intensity of the measures.

V. DISCUSSION

We believe a comprehensive understanding of a complex network such as a bipartite dynamic network is best supported by an animated multi-faceted visualization approach. In this paper we present a network visualization system that supports such an approach.

The Gestalt Principles are good guidelines on how to organize information for easy visual perception. Nesbitt and Friedrich included an excellent explanation of the Gestalt Principles in the context of animated information visualization in their 2002 paper [6]. We will refer to these when explaining our system.

The basis of our system is an iterative node placement algorithm that is based on the force directed graph layout, a natural physical system that is familiar to viewers thus helping with visual perception (Law of Familiarity). The iterative nature of the algorithm allows the intermediate steps to be visualized to assist with comprehension of the formation of the network structure as an evolutionary process (Law of Common Fate, Law of Good Continuation). By fixing the primary nodes the viewer is given a point of reference throughout the animated visualization (Law of Simplicity). The only movements in the visualization are of the secondary nodes, thus simplifying the perceived changes of the network and enabling the viewer to read it as a 1-mode projected visualization (Law of Similarity). The link to the primary nodes can be either drawn or implied with spatial-contextual cues, letting the viewer perceive the influence of the primary nodes on the network (Law of Familiarity).

The node placement calculation is an iterative process that is dependent and highly sensitive to several parameters. We have provided guidelines but highly recommend people using our system to experiment for the best values for their network and application. We have found that even for the same network, tweaking the parameters allowed us to focus on the visualization of different aspects. For example in our case study reducing the attraction factor slowed down the transition phase which produced animations that more resemble people walking in the space. Note the node placement (and their animation) is only an indication of the behavior of the people and is not aimed to model the exact movement of nodes in space-time. For example with the workshop data the time samples are 10 minutes apart, a movement between two locations is visualized as a smooth transition, in reality the person most likely did not take 10 minutes to make the journey: for example any interim stopover of less than 1 minute in duration would have been discarded by the moving filter.

In the case study we have additional information on the affiliations of the secondary nodes. We have only used this information to graphically identify nodes and to imply a collective behavior preference (project preference in work area shown in Fig. 2 and project network connectivity hot spots shown in Fig. 5). Further quantitative analysis could be applied to study the affiliation-dependent behavior and spatial preferences, such as when A from project 1 interacts with B from project 2, do they prefer to do so in neutral territory? Where are the common neutral territories, and how frequently are they used?

We have only experimented with one relatively small social network (containing a total of 23 nodes and 2350 links over 276 time samples). With the workshop interactions the network resulting from proximity data for each time sample was simplified to an un-weighted network. Work remains to extend this system to incorporate link weight. We would also wish to apply this system to additional datasets to refine the parameter guidelines and to test the robustness of the visualizations. We believe our approach is valid for general bipartite networks, and in extension to complex networks.

VI. CONCLUSION

Taking advantage of the distinction of primary and secondary nodes of a bipartite network, we present a novel visualization approach to bipartite networks that considers the primary nodes as sources of attractions that prompt secondary
The overlay method presents an overview of the three network centrality measures mapped onto the floor plan using the node placements. Similar to the overlay visualization in Fig. 2, the project specific color coding allow the viewer to perceive each project as an identity and focus on the distinct project behavior in the spatial context. Inspecting the betweenness measure map tells us that although project 1 worked closely together as group (see explanation for Fig. 2), its members were important to the overall structure of the network, their presence provided critical connections that linked sections of the network together.

The spatial distributions of the degree, closeness and betweenness measures are presented as heat maps. Interpolating the measures over the workshop space produces a more direct spatial perception of the distribution and intensity of the measures. This view is best for presenting the spatial dynamic of the overall network. In this view the difference between the degree distribution and closeness distribution is more obvious: although interactions occurred at almost all work spaces offered to the projects (as perceived from the degree heat map, left), to have a better understanding of the workshop operation one should sit at the center table closer to the door (see the closeness heat map, center). Conveniently this table was not frequently occupied by any of the three projects (see Fig. 2). In reality this was the table that the workshop coordinator chose to use during her office hours.

Nodes to form links to it thus creating the bipartite network. The static primary node placement, corresponding to the spatial attribute of the real-world application when appropriate, enables a force-direct iterative secondary node placement optimization process that also resembles the process of network formation. This enabled the intermediate iterations to be used to assist with the perception of the network structure.

When applied to a dynamic bipartite network our visualization is able to effectively represent the transition movement of the secondary nodes between time samples. The output of our visualization can be presented in many formats including story-
board, animation, or overlaid summary view. The visualization of additional network analysis measures such as the social network centrality measures is also supported. With a real-world social network examples, we successfully demonstrated our network visualization system in action providing animated multi-faceted network presentations for better visual cognition of the network dynamics.

ACKNOWLEDGMENT

This research is funded by the Australian Research Councils Integrating architectural, mathematical and computing knowledge to capture the dynamics of air in design funding scheme (project number DP130103228).

REFERENCES

C. Ethics Documentation Templates

Following is a set of document templates I used when conducting the case studies. Including:

Section C.1 Plan Language Statement (PLS) is to be distributed to targeted participants, describing project brief, data collection and usage, possible risks and benefits, and rights as a participant. The participants sign and return the attached form as a record of consent. Note that participation in the tracking component is optional, see separate Consent Form for Wearable Sensor Tracking form.

Section C.2 Consent Form for Wearable Sensor Tracking is a separate consent for individuals that are participating in the tracking component of the research.

Section C.3 Organisation Agreement lists conditions of data usage, authorship of the project and IP.

C.1. Plan Language Statement to Participants
INVITATION TO PARTICIPATE IN A RESEARCH PROJECT

PARTICIPANT INFORMATION

Application of proximity beacon technologies for understanding behaviour and spatial usage in office spaces, a Multidisciplinary Collaboration in Design project

Investigator:
[Insert: Host contact person and project collaborations]

Mani Williams, PhD Candidate, Spatial Information Architecture Laboratory (SIAL)/Architecture and Design/Design and Social Context/RMIT University, email mani.williams@rmit.edu.au
Associate Professor Jane Burry, Director of Spatial Information Architecture Laboratory (SIAL)/Architecture and Design/Design and Social Context/RMIT University, ph (+613) 99253469, email jane.burry@rmit.edu.au

Dear Sir or Madam,

You are invited to participate in a research project being conducted in RMIT University in collaboration with [Host name]. Please read this sheet carefully and be confident that you understand its contents before deciding whether to participate. If you have any questions about the project, please ask one of the investigators.

Who is involved in this research project? Why is it being conducted?

Application of proximity beacon technologies for understanding behaviour and spatial usage in office spaces (Proximity sensing) is a research project conducted collaboratively between RMIT University (Mani Williams and Jane Burry) and [Host name and list of the people within the organisation that will be involved in the project].

The aim of this project is to investigate proximity sensor based systems and methods for understanding how people interact spatially with each other, as well as how space is utilised in a professional office context. The focus of the project is providing insights for academic research as well as developing a deployable system for industry rollout. The site of this project is [Tracking site location].

This project is an extension of the Multidisciplinary Collaboration in Design project, a PhD research project conducted in SIAL, led by Mani Williams
(PhD Candidate) and supervised by Jane Burry. *Multidisciplinary Collaboration in Design* investigates how knowledge is shared and created in a collaborative design environment, and how each member of the multidisciplinary team contributes to the production of successful design solutions.

This project is jointly supported by [Host name] and the Australian Research Council’s *Integrating architectural, mathematical and computing knowledge to capture the dynamics of air in design* funding scheme (project number DP130103228).

**Why have you been approached?**

We have selected [Tracking site location] as the subject of our research.

You are approached either because you are an employee of [Host name] that will be operating in [Tracking site location] space, or you are associated with the design and development of this space.

Your decision to decline to participant in the *Proximity Sensing* project, or withdraw from the project during the data collection process, will have no effect on your employment or on-going association with [Host name].

You, as a participant in the *Proximity Sensing* project, are being advised via this letter of the potential use of the following in the research team’s future academic or commercial projects, possibly including exhibitions, conference and written papers:

a) Your responses in questionnaires and interviews;

b) The collection of your behaviour data in the activities through a selection of:
   a. Direct observation;
   b. Indirect observation with the use of video and/or still camera, and/or other non-intrusive sensor devices, and/or software applications installed on your personal devices.

**If I agree to participate, what will be required to do?**

Beyond the normal operations that you conduct in the subject area (to be referred to as Activities), you may be required to:

a) Grant your permission for the use of written and visual material of you and/or generated by you during the project activates in future research publications and in other professional documentation contexts of RMIT and [Host name].

b) Participate in the behaviour research component of the project by wearing sensors or install software application on your personal devices. This allows your spatial movements to be tracked while you are conducting your normal daily activities in the space. Those sensors and software can be paused or removed at any time.
c) Participate in focus group discussions, interviews and/or fill out questionnaire relating to the Proximity Sensing project and your Activities.

What are the possible risks and disadvantages?

There are no direct risks of physical or emotional harm as the research team is investigating collaborative processes in the professional context and are only seeking details of your personal experiences within the boundary of your participation in the project activities.

As this project is jointly developed and funded by [Host name], [Host name] will have access to the results from this study. The research team works to protecting your privacy and give you control over your data (see sections What will happen to the information I provide? and What are my rights as a participant?)

What are the benefits associated with participation?

Through your participation in the Project we may discover insights that helps you to improve your work environment.

You will be introduced to the technology and methodology used in the Proximity Sensing research project. The project investigators are happy to discuss the Project in detail, assist and collaborate with you to pursue possible future research in similar areas.

In the larger picture, by participating in this research project you are contributing to the better understanding of the collaborative work environment and future impact of the progress of the design profession.

What will happen to the information I provide?

Your response to the release form will guide the Proximity Sensing research team in the potential use of your material. Refusal of permission for use of your materials or granting a conditional or limited use of your materials will not affect your participation in the project activities. Copies of the research materials and data collected will be kept in a secure location on the RMIT computer server and [Host’s data storage solution] that are only reviewed by the listed investigators. Results from the study may appear in publications, be included in a thesis or report, or be presented at conferences. Any behavioral data collected will be de-identified before publication. De-identified data may be stored in an online database and released to the public.

Specifically:

• The data we collect will never be published or discussed with person or parties outside the listed project investigators in a way that will allow you to be identified.
• We have written agreement from the [Host] management that any results from the project will not be used in any form of employee performance evaluation.

What are my rights as a participant?

• The right to withdraw from participation at any time.
• The right to have any unprocessed data withdrawn and destroyed provided it could be reliably identified.
• The right to have any de-identified data withdrawn from the online database administrated by the investigators.
• The right to have any questions answered at any time.
• Your personal data collected in the course of the research and the results from the study will be available to you on request.

Whom should I contact if I have any questions?

[Host contact’s name and contact information]

Mani Williams, RMIT, email mani.williams@rmit.edu.au
Jane Burry, RMIT, email jane.burry@rmit.edu.au

Yours sincerely

[Host contacts and collaborators]

Mani Williams
Jane Burry

If you have any concerns about your participation in this project, which you do not wish to discuss with the researchers, then you can contact the Ethics Officer, Research Integrity, Governance and Systems, RMIT University, GPO Box 2476V VIC 3001. Tel: (03) 9925 2251 or email human.ethics@rmit.edu.au
PARTICIPANT'S CONSENT

1. I am 18 years old or older.
2. I have had the project explained to me, and I have read the information sheet.
3. I agree to participate in the research project as described:
   a) I agree to the collection of personal and environmental data through the use of photo and voice recording devices, wearable sensors and software applications.
   b) The de-identified data collected from me may be included in a publicly accessible database.
4. I acknowledge that:
   (a) I understand that my participation is voluntary and that I am free to withdraw the use of my written and visual material in research and publication activities; withdraw any unprocessed data previously supplied (unless follow-up is needed for safety) at any time up to the publication of the materials; have any de-identified data withdrawn from the online database administrated by the investigators.
   (b) The use of my written and visual material is for the purpose of research. It may not be of direct benefit to me.
   (c) The privacy of the personal information I provide will be safeguarded and only disclosed where I have consented to the disclosure or as required by law. All use of my work will be credited as I have directed.
   (d) The security of the research data will be protected during and after completion of the study. The data collected during the study may be published, and a report of the project outcomes will be provided on my request.

Participant's Consent
Name:
______________________________________________________________________________________

Signature : ________________________________ Date : ________________________________

If you have any concerns about your participation in this project, which you do not wish to discuss with the researchers, then you can contact the Ethics Officer, Research Integrity, Governance and Systems, RMIT University, GPO Box 2476V VIC 3001. Tel: (03) 9925 2251 or email human.ethics@rmit.edu.au

Data Identification Number: __________________________
C.2. Consent Form for Wearable Sensor Tracking

PARTICIPANT'S INFORMATION

Name:

Contact Email:

ZigBee Tracking tag ID (ie "3B0300"):

Current Project:

Role:

Do you consent to be added to a mailing list to be contacted for follow up questionnaires and project updates? (Please select):

☐ Yes

☐ No

PRIVACY

I authorise and consent to the collection, storage, use and disclosure by [Name of the researchers and collaborators] of images, photographs or written/electronic information about me to be used in the following:

* Incorporated into printed publications to be distributed both locally and internationally

* Made available on various forms of electronic media such as CD-ROM, signage or displays

* To be screened/exhibited publicly as part of RMIT or externally approved exhibitions / events

* I explicitly consent for the de-identified data collected from me to be included in a publicly accessible database

Signature: ___________________________ Date: __________________
C.3. Organisation Agreement

**APPROVAL FOR LOCATION STUDY AT [HOST NAME]**

This agreement is for the collaborative research project between [host name] and Mani Williams. The project will investigate the application of proximity beacon technologies for understanding behavior and spatial usage in office spaces.

**DATA USE**
- Data gathered will not be used to evaluate any individual employee’s performance nor will it be used in decisions pertaining to remuneration, promotion, or employment contracts.
- Data will be de-identified prior to publication.

**AUTHORSHIP**
- Unless otherwise agreed to, Mani Williams, Jane Burry, [host collaborators] will be acknowledged as the authors of the research.
- The project will be identified as collaboration between [host name] and the Spatial Information Architecture Laboratory at RMIT University.
- [Host name] and the Australian Research Council will be acknowledged as sponsors of the research.

**INTELLECTUAL PROPERTY**
- All parties retain their rights to intellectual property that they developed prior to this project.
- Any intellectual property developed during the course of this study will be jointly owned by the authors of the study with [host name] and Mani Williams granted all rights in perpetuity to use the intellectual property.

[Host director’s signature]

[Position]

[Date]

[My signature]

Mani Williams, PhD Candidate, RMIT

[Date]
D. Letters of Ethics Approval from RMIT University

Included are the letters of approval from Design and Social Context College Human Ethics Advisory Network, a sub-committee of the RMIT Human Research Ethics Committee (HREC), to conduct this PhD research.
D.1. Ethics Approval for the Discovery Case Study

I am pleased to advise that your application has been granted ethics approval by the Design and Social Context College Human Ethics Advisory Network as a sub-committee of the RMIT Human Research Ethics Committee (HREC).

Terms of approval:
1. Responsibilities of investigator
   It is the responsibility of the above investigator/s to ensure that all other investigators and staff on a project are aware of the terms of approval and to ensure that the project is conducted as approved by the CHEAN. Approval is only valid whilst the investigator/s holds a position at RMIT University.

2. Amendments
   Approval must be sought from the CHEAN to amend any aspect of a project including approved documents. To apply for an amendment please use the ‘Request for Amendment Form’ that is available on the RMIT website. Amendments must not be implemented without first gaining approval from CHEAN.

3. Adverse events
   You should notify HREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.

4. Participant Information and Consent Form (PICF)
   The PICF and any other material used to recruit and inform participants of the project must include the RMIT university logo. The PICF must contain a complaints clause including the project number.

5. Annual reports
   Continued approval of this project is dependent on the submission of an annual report. This form can be located online on the human research ethics web page on the RMIT website.

6. Final report
   A final report must be provided at the conclusion of the project. CHEAN must be notified if the project is discontinued before the expected date of completion.

7. Monitoring
   Projects may be subject to an audit or any other form of monitoring by HREC at any time.

8. Retention and storage of data
   The investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

In any future correspondence please quote the project number and project title.

On behalf of the DSC College Human Ethics Advisory Network I wish you well in your research.

Suzana Kovacevic
Research and Ethics Officer
College of Design and Social Context
RMIT University
Ph: 03 9925 2974
Email: suzana.kovacevic@rmit.edu.au
Website: www.rmit.edu.au/dsc
I am pleased to advise that your amendment requesting access to a different dataset and to share and publish the new data that is to be collected has been granted ethics approval by the Design and Social Context College Human Ethics Advisory Network as a sub-committee of the RMIT Human Research Ethics Committee (HREC).

Terms of approval:

1. Responsibilities of investigator
   It is the responsibility of the above investigator/s to ensure that all other investigators and staff on a project are aware of the terms of approval and to ensure that the project is conducted as approved by the CHEAN. Approval is only valid whilst the investigator/s holds a position at RMIT University.

2. Amendments
   Approval must be sought from the CHEAN to amend any aspect of a project including approved documents. To apply for an amendment please use the 'Request for Amendment Form' that is available on the RMIT website. Amendments must not be implemented without first gaining approval from CHEAN.

3. Adverse events
   You should notify HREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.

4. Participant Information and Consent Form (PICF)
   The PICF and any other material used to recruit and inform participants of the project must include the RMIT university logo. The PICF must contain a complaints clause including the project number.

5. Annual reports
   Continued approval of this project is dependent on the submission of an annual report. This form can be located online on the human research ethics web page on the RMIT website.

6. Final report
   A final report must be provided at the conclusion of the project. CHEAN must be notified if the project is discontinued before the expected date of completion.

7. Monitoring
   Projects may be subject to an audit or any other form of monitoring by HREC at any time.

8. Retention and storage of data
   The investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

In any future correspondence please quote the project number and project title.

On behalf of the DSC College Human Ethics Advisory Network I wish you well in your research.

Suzana Kovacevic
Research and Ethics Officer
College of Design and Social Context
RMIT University
Ph: 03 9925 2974
Email: suzana.kovacevic@rmit.edu.au
Website: www.rmit.edu.au/dsc
D.3. Ethics Approval for the Deployment Case Study

Date: 25 February 2015
Project number: CHEAN A 0000015704-09/13
Project title: Multidisciplinary Collaboration in Design
Risk classification: Low Risk
Investigator: A/Professor Jane Burry and Mani Williams


I am pleased to advise that the next stage of the project referred to as "Proximity Sensing", addition of two investigators Daniel Davis and Andy Payne and the development of a Bluetooth based indoor tracking system has been granted ethics approval by the Design and Social Context College Human Ethics Advisory Network as a sub-committee of the RMIT Human Research Ethics Committee (HREC).

Terms of approval:

1. Responsibilities of investigator
   It is the responsibility of the above investigator/s to ensure that all other investigators and staff on a project are aware of the terms of approval and to ensure that the project is conducted as approved by the CHEAN. Approval is only valid whilst the investigator/s holds a position at RMIT University.

2. Amendments
   Approval must be sought from the CHEAN to amend any aspect of a project including approved documents. To apply for an amendment please use the ‘Request for Amendment Form’ that is available on the RMIT website. Amendments must not be implemented without first gaining approval from CHEAN.

3. Adverse events
   You should notify HREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.

4. Participant Information and Consent Form (PICF)
   The PICF and any other material used to recruit and inform participants of the project must include the RMIT university logo. The PICF must contain a complaints clause including the project number.

5. Annual reports
   Continued approval of this project is dependent on the submission of an annual report. This form can be located online on the human research ethics web page on the RMIT website.

6. Final report
   A final report must be provided at the conclusion of the project. CHEAN must be notified if the project is discontinued before the expected date of completion.

7. Monitoring
   Projects may be subject to an audit or any other form of monitoring by HREC at any time.

8. Retention and storage of data
   The investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

In any future correspondence please quote the project number and project title.

On behalf of the DSC College Human Ethics Advisory Network I wish you well in your research.

Suzana Kovacevic
Research and Ethics Officer
College of Design and Social Context
RMIT University
Ph: 03 9925 2974
Email: suzana.kovacevic@rmit.edu.au
Website: www.rmit.edu.au/dsc
Notice of Approval

Date: 27 April 2015
Project number: CHEAN A 0000015704-09/13
Project title: Multidisciplinary Collaboration in Design
Risk classification: Low Risk
Investigator: A/Professor Jane Burry and Mani Williams
Approved: From: 27 April 2015 To: 21 September 2016

I am pleased to advise that the inclusion of a participant questionnaire for the "Proximity Sensing" project has been granted ethics approval by the Design and Social Context College Human Ethics Advisory Network as a sub-committee of the RMIT Human Research Ethics Committee (HREC).

Terms of approval:

1. Responsibilities of investigator
   It is the responsibility of the above investigator/s to ensure that all other investigators and staff on a project are aware of the terms of approval and to ensure that the project is conducted as approved by the CHEAN. Approval is only valid whilst the investigator/s holds a position at RMIT University.

2. Amendments
   Approval must be sought from the CHEAN to amend any aspect of a project including approved documents. To apply for an amendment please use the 'Request for Amendment Form' that is available on the RMIT website. Amendments must not be implemented without first gaining approval from CHEAN.

3. Adverse events
   You should notify HREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.

4. Participant Information and Consent Form (PICF)
   The PICF and any other material used to recruit and inform participants of the project must include the RMIT university logo. The PICF must contain a complaints clause including the project number.

5. Annual reports
   Continued approval of this project is dependent on the submission of an annual report. This form can be located online on the human research ethics web page on the RMIT website.

6. Final report
   A final report must be provided at the conclusion of the project. CHEAN must be notified if the project is discontinued before the expected date of completion.

7. Monitoring
   Projects may be subject to an audit or any other form of monitoring by HREC at any time.

8. Retention and storage of data
   The investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

In any future correspondence please quote the project number and project title.

On behalf of the DSC College Human Ethics Advisory Network I wish you well in your research.

Suzana Kovacevic
Research and Ethics Officer
College of Design and Social Context
RMIT University
Ph: 03 9925 2974
Email: suzana.kovacevic@rmit.edu.au
Website: www.rmit.edu.au/dsc
Notice of Approval

Date: 17 September 2015
Project number: CHEAN A 0000015704-09/13
Project title: Multidisciplinary Collaboration in Design
Risk classification: Low Risk
Investigator: A/Professor Jane Burry and Mani Williams

Approved: From: 17 September 2015 To: 21 September 2016

I am pleased to advise that the access of an existing data set as part of the “Proximity Sensing” project has been granted ethics approval by the Design and Social Context College Human Ethics Advisory Network as a sub-committee of the RMIT Human Research Ethics Committee (HREC).

Terms of approval:

1. Responsibilities of investigator
   It is the responsibility of the above investigator/s to ensure that all other investigators and staff on a project are aware of the terms of approval and to ensure that the project is conducted as approved by the CHEAN. Approval is only valid whilst the investigator/s holds a position at RMIT University.

2. Amendments
   Approval must be sought from the CHEAN to amend any aspect of a project including approved documents. To apply for an amendment please use the ‘Request for Amendment Form’ that is available on the RMIT website. Amendments must not be implemented without first gaining approval from CHEAN.

3. Adverse events
   You should notify HREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.

4. Participant Information and Consent Form (PICF)
   The PICF and any other material used to recruit and inform participants of the project must include the RMIT university logo. The PICF must contain a complaints clause including the project number.

5. Annual reports
   Continued approval of this project is dependent on the submission of an annual report. This form can be located online on the human research ethics web page on the RMIT website.

6. Final report
   A final report must be provided at the conclusion of the project. CHEAN must be notified if the project is discontinued before the expected date of completion.

7. Monitoring
   Projects may be subject to an audit or any other form of monitoring by HREC at any time.

8. Retention and storage of data
   The investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

In any future correspondence please quote the project number and project title.

On behalf of the DSC College Human Ethics Advisory Network I wish you well in your research.

Suzana Kovacevic
Research and Ethics Officer
College of Design and Social Context
RMIT University
Ph: 03 9925 2974
Email: suzana.kovacevic@rmit.edu.au
Website: www.rmit.edu.au/dsc


Bibliography


Bibliography


237


Pan, G. et al. (2013). “Trace analysis and mining for smart cities: Issues, methods, and applications”. In: IEEE Communications Magazine 51.6, pp. 120–126. ISSN: 0163-6804. DOI: 10.1109/MCOM.2013.6525604.


239
Bibliography


Salim, Flora et al. (2014). “Visualization of wireless sensor networks using ZigBee’s Received Signal Strength Indicator (RSSI) for indoor localization and tracking”. In: Pervasive computing and communications workshops (PERCOM workshops), 2014 IEEE international conference on. IEEE, pp. 575–580.


Waber, Benjamin N and Alex Sandy Pentland (2009). “Recognizing expertise”. In: *Winter Conference on Business Intelligence, University of Utah, Utah, USA*.


Bibliography


Williams, Mani, Jane Burry, and Asha Rao (2015a). “Graph mining indoor tracking data for social interaction analysis”. In: Pervasive Computing and Communication Workshops (PerCom Workshops), 2015 IEEE International Conference on. IEEE, pp. 2–7.


