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Particle Filter based Multi-sensor Data Fusion Techniques for RPAS Navigation and Guidance

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Abstract—This paper presents a Particle Filter (PF) based Multi-Sensor Data Fusion (MSDF) technique in an integrated Navigation and Guidance System (NGS) design based on low-cost avionics sensors. The performance of PF based MSDF method is compared with previous implemented multi data fusion architectures for small-sized Remotely Piloted Aircraft Systems (RPAS). The sensor suite of the implemented NGS includes: Global Navigation Satellite System (GNSS) sensor, which is adopted as the primary means of navigation, Micro-Electro-Mechanical System (MEMS) based Inertial Measuring Unit (IMU) and Vision-Based Navigation (VBN) sensor. Additionally, an Aircraft Dynamics Model (ADM) is used as a virtual sensor to compensate for the MEMS-IMU sensor shortcomings in high-dynamics attitude determination tasks. The PF is specifically implemented to increase the accuracy of navigation solution obtained from the inherently inaccurate, low-cost Commercial-Off-The-Shelf (COTS) sensors. Simulations are carried out on the AEROSONDE RPAS performing high-dynamics manoeuvres representative of the RPAS operational flight envelope. The Extended Kalman Filter (EKF) based VBN-IMU-GNSS-ADM (E-VIGA) system, Unscented Kalman Filter (UKF) based U-VIGA system and the PF based P-VIGA system performances are evaluated and compared. Additionally, an error covariance analysis is performed on the centralised filter using Monte Carlo simulation. Results indicate that the PF is computationally expensive as the number of particles is increased. Compared to E-VIGA and U-VIGA systems, P-VIGA system shows an improvement of accuracy in the position, velocity and attitude measurements.

Keywords—Remotely Piloted Aircraft Systems; Aircraft Dynamics Model; Particle Filter; Unscented Kalman Filter; Low-Cost Avionics Sensors; Global Navigation Satellite System.

I. INTRODUCTION

In recent times, the adoption of Remotely Piloted Aircraft Systems (RPAS) in civil and military applications has increased considerably. In order to enable RPAS to co-exist with manned aircraft, technological advances are envisaged as part of the Communications, Navigation, and Surveillance (CNS)/Air Traffic Management (ATM) and avionics (CNS+A) framework. Such recent advancements are focused towards addition or improvements in systems and functionalities, which are providing solutions to integrate RPAS into non-segregated airspace. The International Civil Aviation Organization (ICAO) operating as a specialized agency of the United Nations (UN) has developed an evolutionary roadmap to facilitate engineers and air service providers with the development and harmonization of avionic capabilities and ATM ground infrastructure. The roadmap has identified Aviation System Block Upgrades (ASBU) that provides key consecutive steps towards global interoperability. Accordingly, RPAS will require enhanced navigational capabilities in order to meet the Required Navigational Performance (RNP) and Reduced Vertical Separation Minima (RVSMin) expected of manned aircraft. Additionally, the integration is foreseen by providing cooperative and non-cooperative Sense-and-Avoid (SAA), Line-Of-Sight (LOS) / Beyond LOS (BLOS) data links and continuous airworthiness as depicted in Fig. 1 [1].

![Integration of RPAS into Non-segregated Airspace](image)

**Fig. 1.** Requirements for RPAS and manned aircraft co-existence.

The exchange of aeronautical data and messages between aeronautical users and/or automated systems is the communications element of CNS/ATM systems and it also provides support for specific navigation and surveillance functions [2]. Systems that enhance safety and integrity gain significant importance and need to be addressed to a greater extent [3, 4]. Navigation systems are becoming increasingly driven by Performance Based Navigation (PBN) criteria. Furthermore, Global Navigation Satellite System (GNSS) is increasingly influential due to its worldwide coverage and accurate time determination in all weather conditions. To overcome inherent system limitations and to meet the
performance requirements (accuracy, integrity, availability and continuity of service) for all phases of flight, different constellations including Global Positioning System (GPS) and GLObal NAVigation Satellite System (GLONASS) require varying degrees of augmentation [2]. Therefore, a number of augmentation systems including aircraft-based, ground-based and satellite-based augmentations are being developed to address the shortcomings of the GNSS solution, primarily during loss of lock conditions.

Our research focuses on developing a low-cost Navigation and Guidance System (NGS) for RPAS, which is primarily based on satellite and inertial sensors. High-integrity airborne and ground-based integrated NGS that incorporate fail-safe architecture designs are required to meet RNP criteria [5]. The selection of the navigation sensors is based on the requirements of low-cost, low-weight/low-volume sensors capable of providing the required level of performances in all flight phases of a small-sized RPAS including high dynamics manoeuvres. GNSS and Micro-Electro-Mechanical System (MEMS) based Inertial Measuring Unit (IMU) are a highly synergistic combination of navigation sensors capable of providing an accurate navigation state vector better than any single sensor [5]. Vision-Based Navigation (VBN) sensors are specifically used for precision approach and landing (i.e., the most demanding and potentially safety-critical flight phase) [6]. Aircraft Dynamics Model (ADM) is a knowledge-based module and is used as a virtual sensor to augment the navigation state vector in high dynamics attitude determination tasks [6]. When pre-processed with estimation techniques, the ADM estimates the true RPAS flight dynamics (aircraft trajectory and attitude motion) [7]. New methods of sensing the surrounding environment are also under development including bio-inspired pressure sensing technology which allows for the direct measurement of turbulence [8]. Measuring turbulence directly allows for an advantageous time forward response and can be performed using a limited number of pressure sensors [9]. The effects of turbulence on RPAS are well known and by mitigating the effects of low atmospheric turbulence before it directly affects the aircrafts attitude, the navigation and tracking performance can be improved [9]. Three filters are used in the implemented low-cost NGS including Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Particle Filter (PF). The EKF is the most widely applied state estimation algorithm for non-linear systems [10]. However, the EKF can be difficult to tune and often provides unreliable estimates if the system non-linearities are severe, the reason being EKF relies on linearization to propagate the mean and covariance of the state [11]. The UKF is based on the sigma point family of non-linear approximation filters. In our previous research, it was shown that the UKF achieved slightly better accuracy than the EKF due to its superior performance with high non-linearities [5]. The PF is developed to provide a complete and robust description of the navigation state vector of the RPAS platform in real-time. The PF copes much better than the traditional filters with non-linear models and has no limitations when it comes to the non-linearity of the application including non-Gaussian noise [13]. PF are sequential Monte Carlo methods based on point mass representations of probability densities, which can be applied to any state-space model [14]. The key feature of a PF is that it constructs conditional probability of the variable to be estimated, with respect to the measurements, through a suitable random particle exploration of the state space followed by Bayes correction of weights of the particles [13]. In the proposed NGS architecture, the filters process the non-linear measurements and processes models of the NGS sensors [7]. Additionally, the PF also pre-filters the ADM data taking into account the non-linear aircraft motion and thus increases its attitude solution validity time. A comparison of the performance characteristics of the filters considered is summarised in Table I. The performance of the PF varies depending on the number of particles used.

<table>
<thead>
<tr>
<th>Performance Characteristic</th>
<th>EKF</th>
<th>UKF</th>
<th>PF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>High</td>
<td>High</td>
<td>Very High</td>
</tr>
<tr>
<td>Stability</td>
<td>Moderate</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Computational Cost</td>
<td>High</td>
<td>Low</td>
<td>Moderate</td>
</tr>
<tr>
<td>Convergence Rate</td>
<td>Moderate</td>
<td>Fast</td>
<td>Fast</td>
</tr>
<tr>
<td>Implementation Complexity</td>
<td>Difficult</td>
<td>Moderate</td>
<td>Moderate</td>
</tr>
</tbody>
</table>

II. MULTI-SENSOR DATA FUSION

Multi-Sensor Data Fusion (MSDF) is the process of combining observations from a number of sensors to provide a robust and complete description of an environment or process of interest [15]. The act of combining multiple sensors is used to derive an estimate, which has better performance than the one that is obtained from a single sensor. The sources of measurement are obtained most often from sensors and systems, which measure a specific variable of interest in order to derive a desired output from the system. In certain cases, a variety of sensors are used to measure either the same or different variables. Non-linear systems require approximation techniques to predict or estimate the solution of the non-linear measurement. Some notable forms of non-linear approximation techniques include; the most popular EKF, sigma point based filters such as the sigma point Kalman filter, the UKF and the square root sigma point Kalman filter and Monte Carlo methods such as the PF. The PF is based on sampling and resampling processes and its variations include the Rao-Blackwellized PF, the unscented PF, auxiliary PF and many more. In case of non-linear filtering problems addressed by PF, inferences are made based on the observations to obtain the hidden variables. In the Bayesian framework, this is performed by approximating the posterior distribution for the state vector, given all available observations at any specific time instance [16]. In the case of navigation applications, given the observations, the above notion provides a basis for determination of RPAS platform position with a conditional probability density function.

A. The Particle Filter

Applied non-linear filtering is based on discrete time state space models relating a hidden state, \( x_k \) to the observation, \( y_k \) given by:

\[
x_{k+1} = f(x_k, u_k) + Q.
\]

(1)
where $Q$ is the process noise and $R$ is the measurement noise. In this system description, $x_k$ is the state vector and $u_k$ is the control vector. The EKF and the UKF are sub-optimal when linearizing a non-linear system. These two filters rely on Gaussian approximations while the PF does not require this assumption. The PF is a general Monte Carlo (sampling) method for performing inference in state-space models where the state of a system evolves over time and information about the state is obtained via noisy measurements made at each time step [16]. The prediction/estimation steps are used to obtain new measurements sequentially as opposed to EKF and UKF. The fundamental idea is to represent the model to generate the posterior density by a set of random particles with associated weights and the estimate is computed based on samples and their associated weights after being transformed through the non-linear function. When employing a PF, the more non-linear the model, or the more non-Gaussian noise, the more potential PFs have, especially in applications where computational power is rather cheap and the sampling rate is moderate [16]. The PF is considered as an alternative for real-time applications, which are typically approached by model-based traditional Kalman filter technique implementations [16]. The PF approximates the optimal solution numerically based on a physical model, rather than applying an optimal filter to an approximate model [16]. PFs are attractive because they do not require a fixed computation time; instead, their accuracy increases with the available computational resources. Most importantly, they are relatively easier to be implemented. The realisation of PF does not require the process of linearizing non-linear models, or the need to worry about closed-form solutions. A well-known problem with the PF is that its performance degrades quickly when the dimension of the state dimension increases. The main drawback of PF is that, for populating a dimensional space, it requires exponentially many particles [18]. Most successful applications have therefore been confined to low-dimensional state spaces. The utilization of structure (e.g., conditional independences), present in many robotics problems, has recently led to applications in higher dimensional spaces [18]. The advantages and disadvantages of the PF are summarised in Table II.

### Table II. PF advantages and disadvantages.

<table>
<thead>
<tr>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approximate solution numerically from physical model</td>
<td>Computational expensive when large number of particles are considered</td>
</tr>
<tr>
<td>Approximate Bayesian posterior probability density function with set of randomly chosen weighted samples</td>
<td>The most efficient number of particles cannot be calculated</td>
</tr>
<tr>
<td>Large number of samples guarantees almost sure convergence to the true probability density function</td>
<td>Distributions are only approximated which leads to calculation errors</td>
</tr>
<tr>
<td></td>
<td>High computational burden</td>
</tr>
</tbody>
</table>

B. Algorithm

When using the PF, the state is predicted based on a set of particles, which are generated at time $k$ and they are assigned individual weights based on the initial value of each particle in relation to the non-linear function. In the resampling phase, a new set of particles are derived from the discrete approximation of the filter distribution function provided by the weighted particles phase. The algorithm operates online while estimating the posterior density of the state space. The generated samples from the required distribution require no assumptions to be made when the state space model is either linear or non-linear. Sequential Importance Sampling (SIS) is prone to divergence because after a few iterations most particles have negligible weights and it leads to the degeneracy phenomenon. Therefore the evolution of SIS is the Sequential Importance Resampling (SIR) algorithm. The SIR algorithm uses the resampling method that incorporates a threshold to eliminate sampled particles, which fall outside of this threshold. Specifically particles with low importance weights are given by:

$$\{x_k^i, w_k^i\}_{i=1}^N \rightarrow \{x_k^i, w_k^i\}_{i=1}^N$$

where $w_k^i$ are the weights. The particles associated with low importance weights are eliminated. The PF algorithm is illustrated in Fig. 2, in which the larger finite circles (red) represent the particles with greater weightings.

![Fig. 2. Particle filter algorithm.](image)

The steps involved in computing the best estimate Position, Velocity and Attitude (PVA) measurements are described below:

1. Initialization:

   Initialization of the PF is performed by generating a number, $N$ of particles, $p_{x_0}$ along with a non-linear model, $x_k^i$ at each time step, $k$. The particles are represented by $X_0$ and
are generated at time, \( k = 0 \), based on the following conditions:

“Generate \( x_1^i \sim p_{x_0} \) where \( i = 1, 2, \ldots, N \) and let \( w_{10}^i = 1/N \) where \( k = 1, 2, \ldots, n \).” \( i \) and \( j \) represent the sampled and resampled particles respectively. The generation of \( N \) particles, or sample of the state vector, \( X_0^i \), with equal weights \( 1/N \) is then performed [16].

**Sampling**

Samples are not drawn according to \( p(x(k)|z_{0:k}) \) directly, but are drawn from an importance (probability density) function. In the sample \( \hat{x}_k^{(i)} \sim q(x_k|x_{0:k-1}, y_{1:k}) \) where \( \hat{x}_k^{(i)} \neq \left(x_{0:k-1}^{(i)}, \check{x}_k^{(i)}\right) \) and \( i = 1, \ldots, N \). For \( i = 1, \ldots, N \), evaluate the importance weights up to a normalizing constant:

\[
w_k^{(i)} = w_k^{(i)} \frac{p(x_k|x_{0:k}^{(i)})p(z_k|\hat{x}_k^{(i)})}{q(x_k|x_{0:k-1}^{(i)}, y_{1:k})} \tag{4}
\]

For \( i = 1, \ldots, N \), normalized importance weights are given by:

\[
\tilde{w}_k^{(i)} = \frac{w_k^{(i)}}{\sum_{j=1}^{N} w_k^{(j)}} \tag{5}
\]

**Prediction:**

\( X_{k+1}^i \) are estimated based on the RPAS dynamics.

**Measurement update:**

The update of weights for \( i = 1, \ldots, N \) is according to:

\[
w_{k|i}^i = \frac{1}{c_k} w_{k|i-1}^i p(y_k|x_k^i) \tag{6}
\]

**Normalization of the weights:**

The normalization weight is given by:

\[
c_k = \sum_{i=1}^{N} w_{k|i-1}^i p(y_k|x_k^i) \tag{7}
\]

The measurement update consists of the particle/state estimate update along with the associated weights and the observation for that instant in time.

\[
w_k^i = \frac{w_{k|i}^i}{\sum_{i=1}^{N} w_{k|i}^i} \tag{8}
\]

Before resampling, normalizing of the probability distribution function is performed.

2. Resampling:

Resampling is required to restrict samples with non-zero weights. A degeneracy problem may be experienced after a few steps, rising from a particles becoming unacceptable. The level of degeneracy is estimated based on the variance of weights. In order to prevent high concentration of probability mass on only a few particles (leading to the convergence of a single \( w_k^i \) to 1), particles are resampled using:

\[
\frac{1}{\sum_{i=1}^{N} [w_k^i]} < 0.5 N \tag{9}
\]

In the resampling stage, samples \( \hat{x}_{0:k}^{(i)} \) with higher weights \( \tilde{w}_k^{(i)} \) are chosen and those with lower weights are inhibited. To obtain \( N \) random samples \( x_{0:k}^{(i)} \) approximately distributed according to \( p(x_{0:k}^{(i)}|y_{1:k}) \).

3. Output Estimation:

The PF output generates a set of samples, which are used to approximate the posterior distribution which is given by:

\[
p(x_{0:k}|y_{1:k}) \approx \hat{p}(x_{0:k}|y_{1:k}) = \frac{1}{N} \sum_{i=1}^{N} \delta(x_{0:k}^{(i)})dx_{0:k} \tag{10}
\]

An estimate \( \mathbb{E}(g_k(x_{0:k})) \) is thus obtained by:

\[
\mathbb{E}(g_k(x_{0:k})) = \int g_k(x_{0:k})p(x_{0:k}|y_{1:k})dx_{0:k} \approx \frac{1}{N} \sum_{i=1}^{N} g_k(x_{0:k}^{(i)}) \tag{11}
\]

For a function of interest \( g_k: \mathbb{R}^{n_k} \rightarrow \mathbb{R} \) that is integrable with respect to \( p(x_{0:k}|y_{1:k}) \). The marginal conditional mean is often the quality of interest, because it is the optimal Minimum Mean Square Error (MMSE) estimate of the current state of the system. The new set is generated by sampling with replacement from the discrete representation of \( p(x_k|x_{0:k}) \) such that \( pr\{x_k^i = x_k^j\} = w_k^i \). The resampling process requires to generate \( N \) independent and identically distributed random variables and sort them in an ascending order. This is then compared to the cumulative sum of the normalized weights.

### III. System Architecture

The PF based VBN-IMU-GNSS-ADM (P-VIGA) architecture is illustrated in Fig. 3. The EKF based E-VIGA, UKF based U-VIGA and PF based P-VIGA systems use VBN at 20 Hz and Global Positioning System (GPS) at 1 Hz to augment the MEMS-IMU running at 100 Hz. The architectures includes ADM (computations performed at 100 Hz) to provide attitude channel augmentation. The sensor measurements are handled by a sensor processing and data sorting block. The data sorting algorithm is based on Boolean Decision Logics (BDL), which allow automatic selection of the sensor data based on pre-defined priority criteria.

The sorted data is then fed to the MSDF filter to obtain the best estimate values. The INS position and velocity are compared with the GPS position and velocity to form the measurement input of the data fusion block containing the filter. The attitude data provided by the ADM and the INS are compared to feed the filter at 100 Hz, and the attitude data provided by the VBN sensors and INS are compared at 20 Hz and form the inputs to the EKF. The filter provides estimates of PVA errors, which are then removed from the sensor measurements to obtain the corrected PVA states. An additional UKF/PF is also used to pre-process the ADM navigation solution. The pre-filtering of the ADM virtual sensor measurements aids in achieving reduction of the overall position and attitude error budget and allows a considerable reduction in the ADM re-initialisation time. The PVA measurements are obtained as state vectors from both the centralised filter and Aircraft Dynamics Filter (ADF).
IV. SIMULATION CASE STUDY

A detailed case study was performed in a high dynamics RPAS environment, employing a six-Degree-of-Freedom (6-DoF) model of the AEROSONDE RPAS. The corresponding U-VIGA and P-VIGA integrated navigation modes were simulated using MATLAB\textsuperscript{TM} in an appropriate sequence of flight manoeuvres representative of the AEROSONDE RPAS operational flight envelope. The duration of the simulation is 1700 seconds covering nine flight legs (i.e., take off, straight climb, left climb helix, straight and level cruise, right step down cruise, straight and level cruise, left hand descent, right hand descent and final straight approach) from starting point to destination. The 3D trajectory plot of the flight profiles of AEROSONDE RPAS is illustrated in Fig. 4.

![Fig. 3. P-VIGA architecture.](image)

Fig. 3. P-VIGA architecture.

Fig. 4. 3D trajectory plot of RPAS flight profile.

To extract the relevant information about the performance of the filter, a Monte Carlo simulation (i.e., error covariance analysis) is performed in MATLAB\textsuperscript{TM} and Simulink for 100 iterations with the duration of 50 seconds for each run. The performance analysis is carried out on the centralised filter. The simulation was set up using different noise seeds based on the specificities of the Monte Carlo technique. The performance of the filter is based on the condition that the mean and standard deviation errors remain close to zero. Fig. 5 illustrates the results of the error covariance analysis performed on the primary filter. Each filter has an associated computational time, the processing time for each filter was found to be as follows; the EKF takes 0.1172 seconds, the UKF is the quickest taking 0.0015 seconds and the PF takes 0.0457 seconds for 1000 propagated particles. The simulations were executed on the Windows 7 Enterprise platform (64-bit operating system) supported by the Intel Xeon X5675 CPU with clock speed 3.07 GHz and 3.0 GB RAM. The mean, \( \mu \) and standard deviation, \( \sigma \) of the east position error is illustrated in Fig. 5, 6 and 7 respectively for the EKF, UKF and PF.

![Fig. 5. E-VIGA position error.](image)

Fig. 5. E-VIGA position error.

![Fig. 6. U-VIGA position error.](image)

Fig. 6. U-VIGA position error.
Simulation results demonstrate that correct filter performance of the MSDF was obtained without any divergence. The computational burden of the PF was observed to be large and it increases drastically when more than 1000 particles were used. Due to the increased accuracy in PVA measurements obtained from the PF, it is observed that the performance of the PF is better when compared to EKF and UKF. Hence the PF promises to be a better alternative for low-cost and real-time NGS applications.

V. CONCLUSION

The research activities performed to design a low-cost and low-weight/volume integrated NGS suitable for small-sized RPAS applications were presented. A number of state-of-the-art sensors were considered for the NGS design including GNSS and MEMS-IMU, with augmentation from ADP and VBN sensors. Three different low-cost and low-weight/volume integrated NGS were designed, implemented and compared. They were the EKF based E-VIGA, UKF based U-VIGA and PF based P-VIGA systems. While the E-VIGA system uses unfiltered ADM data, the U-VIGA and P-VIGA systems employ a UKF/PF for pre-filtering the ADM attitude solution and hence an increase in the ADM solution validity time is obtained. Simulation of the E-VIGA integrated navigation mode showed that the integration schemes can achieve horizontal/vertical position accuracies, with a significant improvement compared to stand-alone GNSS and integrated GNSS/IMU. Compared to E-VIGA, U-VIGA and P-VIGA systems showed improvements in PVA measurements in addition to an increased ADM validity time. The performance of each filter was evaluated by performing Monte Carlo runs. It was observed that all the three filters performed correctly with no divergence and the PF shows promising results due to the increase in performance it offers. Further studies will be performed in the future using other advanced filters as the Aircraft Dynamics Filter (ADF). Future research activities will also include uncertainty analysis and possible synergies of the E-VIGA, U-VIGA and P-VIGA architectures with GNSS avionics based integrity augmentation systems [19, 20].

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