A Comparative Performance Analysis of Filtering and Smoothing Techniques on a Simulated Unmanned Aircraft System

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Abstract

In order for unmanned aircraft systems (UAS) to fly safely into civil airspace, the development of vigorous unmanned aircraft's Accident Avoidance System (UAS-AAS) is rather crucial. However, accurate localization is a key prerequisite for a UAS-AAS to be successful. This paper investigate the application of two filtering and smoothing techniques to a UAS given the aircraft dynamics, sensor performance, and the environment in which the aircraft operate. The navigational system provides data of position, velocity and noise. Navigational data is randomly generated. The estimated position of the UAS is then determined by applying the Kalman filtering, Kalman smoothing, Particle filtering and Particle smoothing. The experimental result shows that irrespective of the errors in the measurements, both techniques perform well in estimating the true position of the system. However, the smoothing techniques show the higher accuracy of the results due to the use of more future data than filtering technique.

Keywords: Unmanned aircraft system, Kalman filtering, Kalman smoothing, particle filtering, particle smoothing, Accident Avoidance system

1 Introduction

Unmanned Aircraft Systems (UASs) have been in existence for many years. However, recently the use of UASs has experienced immense growth and play a central role in scientific research, defense and in certain industries [1] and [2]. In history, the use of UAS technologies lie at the core of military operations such as spacecrafts, aircrafts, helicopters, free-flying robots or mobile robots, surveillance, target identification and designation, mine detection, and reconnaissance [1] and [2]. As their use continues to evolve, research has peaked on this technology to discover its applicability to other domains. UAS technologies are categorized as safety critical systems. This is due to them being employed in high-risk tasks that require rigorous development methodologies to assure its integrity. A system that is defined as safety critical can have serious ramifications if a fault occurs. These implications include the risk of injury, loss of life, data, and property. According to National Transport Safety Board (NTSB), injury and damage by NTSB classification for U.S. Air carriers operating under 14 CFR 121 for the year 2012 is 16 and 11 respectively, see Table 1 [3].

	Accidents			
Year	Major	Serious	Injury	Damage
2008	4	1	8	15
2009	2	3	15	10
2010	1	0	14	14
2011	0	0	19	12
2012	0	0	16	11

Table 1: Accident by NTSB Classification, 2008 through 2012 for U.S. Air Carriers Operating Under CFR 121

Definition of NTSB Classifications:
Major - an accident in which any of the three conditions are met:
a part 121 aircraft was destroyed or there were multiple fatalities or there was one fatality and a part 121 aircraft was substantially damaged.
Serious - an accident in which at least one of the two conditions are met:
There was one fatality without substantial damage to a part 121 aircraft or there was at least one serious injury and a part 121 aircraft was substantially damaged.
Injury - a nonfatal accident with at least one serious injury and without substantial damage to a part 121 aircraft
Damage - an accident in which no person was killed or seriously injured, but in which any aircraft was substantially damaged

Unmanned aircraft are not currently permitted access to civil airspace in the United States without special permission from the Federal Aviation Administration (FAA). One of the primary concerns with integrating unmanned aircraft is their inability to robustly sense and avoid other aircraft [6]. In order for UASs to fly safely into civil airspace, the development of vigorous unmanned aircraft's Accident Avoidance Systems (UAS-AAS) is rather crucial. However, accurate localization is a key prerequisite for an AS-AAS to be successful. Therefore, keeping track of these systems is of paramount importance.

By definition, navigation is a process of determining the current parameters of movement, like accelerations, velocity and position of center of mass, of the moving object. The system that provides us with navigational criterion is called Navigation System. One of the most used Navigation Systems, which is designed for a wide range of vehicles, is the Inertial Navigation System (INS). Other system, which is the most famous, is the Global Positioning System (GPS). However, several errors are associated with the GPS measurement [13]. It has superior long-term error performance, but poor short-term accuracy. To ensure high accuracy of monitoring, data is fused to combine measurements from GPS and INS. The short term accuracy of INS is good and the long-term accuracy is poor. If the signal of GPS is hampered, the INS enables availability of data until GPS signal is reestablished [14].

To detect any unexpected change in real time, the Kalman filtering (KF) is used. In 1960 Rudolph E. Kalman published an article describing a recursive solution to the discrete-data linear filtering problem [4]. Since then, as a result of advances in digital computing, the Kalman filtering has been the subject of extensive research and applications, particularly in the area of autonomous or assisted navigation [5]. The Kalman filtering (KF) is a set of mathematical equations that provides an efficient computational means to recursively estimate the state (position and velocity, for example) of a physical system from noisy observation over time. Specifically, the aircraft might be specified by position (A,B,C) and velocity (A`,B`,C`) at each point in time. The next state X_{t+1} is a linear function of the current state X_t, plus some Gaussian noise.

The Kalman filter performs well in tracking a linear system, but it often misses the object when the object changes its direction in an extremely short timeframe. In situations where the problem is nonlinear or the noise that distorts the signal is non-gaussian, the kalman filtering/smoothing (KS) provides a solution that is far from optimal [17]. As a result of its limitation, numerous fixes and modifications have been proposed by researcher for the Kalman filter/smoothing. Proposed methods provide better estimates about the process variable [15]. In this case, the particle filtering (PF)/smoothing (PS) is used due to its excellent performance in difficult situations including communications, signal processing, navigation and computer vision.

Particle filtering are sequential Monte Carlo methods that are used in numerous problems where time-varying signals must be presented in real time; and where the objective is to estimate various unknowns of the signal and/or detect events described by the signals

[17]. Implementing both filtering / smoothing algorithms allows accurate estimation in the position of the unmanned aircraft vehicle (UAV) system whether it behaves linear or nonlinear.

The purpose of this paper is to demonstrate that Kalman filtering/smoothing and particle filtering/smoothing performs well in tracking UAS systems. By gathering information and storing it in a database. This allows systems to both store and retrieve past, present, and future information in the context of physical locality and direction of gaze. A comparison is also provided of the localization accuracy between the KF/KS implementation and the PF/PS implementation.

2 Related Work

As with many things in history, it is difficult to pinpoint a single defining moment when the Kalman filter was first used in virtual reality (VR). This stems from the fact that there was no clear definition of VR and when the use of VR was borned. Flight simulators are usually seen as VR systems, and their development goes back to the early 1960s especially considering digital display [8]. However, it was not until the mid 1980s Kalman filter was documented as being used along with VR [9] and [10]. This work is relevant in that it gave rise to the development of the Space Synchro (SPASYN) magnetic head-tracking technique [11]. It gives rise to the primary means for head tracking in VR today.

In 1988, Rebo’s masters thesis implemented predictive head mounted display (HMD) tracking using Kalman filters on the full 6 degree of freedom (DOF) estimates from the Polhemus system [12]. While the contribution is profound, it is interesting that researcher consider the Kalman filter as a tool for improving motion prediction.

BARAA MUNQITH ALBAKER et al. in their study of developing a functional architecture for unmanned aircraft collision avoidance system, defined an approach based upon flight plan sharing, and cooperatively avoids potential conflict through multi-agent peer to peer aircraft negotiation and predefined maneuvering in heading and speed changes. The researchers consider a team of cooperative and homogeneous UASs. For instance, UAS sharing same airspace and instance, and same altitude. The predefined maneuver is depending directly on the identification of relative collision angle between colliding aircraft. The angle is computed by comparing flight plans of computing and conflicting agents in the near-future and estimate the angle at a time when aircraft's protected zone overlapping is reported.

The developed functional architecture allows each aircraft to negotiate with each other to determine a safe and acceptable resolution when a potential conflict is detected. The proposed approach uses simple negotiation peer to peer protocol to solve the conflicts between two aircraft. This peer to peer approach can be extended to consider multiple collisions among more than two aircraft through iterative utilization of the approach. The simplicity in the mathematics leads to fast computing algorithm.

Thus conflict resolution will be obtained quickly allowing it to be implemented in time critical situations [7]. The problem with their approach is that the approach depends solely on radar sensor and collision avoidance system. It does not utilize noise as the Kalman Filter does. Hence, calculation had to be performed for four sectors (that is, Sector A-course sector; Sector B-left side collision; Sector C-Right side collision; and Sector D -Rear collision. It also raises the question as it relates to the overhead of performing four separate calculations at any point in time.

In the paper entitled Mobile Robot Position Estimation using Kalman filter, the researchers implement KF and extended kalman filter (EKF) for determining the position of a mobile robot [19]. Irrespective of the error in measurement the filters were successful in estimating the robot's' true position.

Robert. J Pawlak in his study combined unscented kalman and particle filtering for tracking closely spaced object. Particle filter was used to estimate the probability density of objects within a group track. A bootstrap particle filter was employed, in which the update was accomplished through a straightforward propagation of the particles through the state space. Particles were updated based on the assumption that each particle corresponds to a tracked object, which travels with same velocity as the group. Nonetheless, individuals object within the group does not always move in perfect synchrony with the centroid of the group. As a result, a small noise (ϵ) term is added to account for the uncompensated movement. The result can be envisioned as a probability density function (PDF), which can be compared to the original PDF sensor measurement [18].

3 Methodology

In this propose architecture, the unmanned aircraft vehicle (UAV) is equipped with GPS/INS and some control algorithm. Initial information such as identification of vehicle, flight plan and intention with cooperative target on UAS is garnered from the central repository. Each system monitors the environment through a periodical calculation on its surroundings and stores the information in a shared repository. The database then uses the calculated data from the computing aircraft to figure out the collision parameters. This sharing of information allows UAV to predict an occurrence of a conflict at some point in time. If a possible impact is detected in the near future, the aircraft then selects a suitable maneuvering command for both computing and conflict, based on the received information from the database. This functionality is considered to be a part of a system known as the unmanned aircraft's Accident Avoidance System (UAS-AAS). Fig. 1 shows the UAS-AAS functionalities. The system also interacts with an external database. The external database is referred to as a duplicate database, which interacts with the UAS-AAS local database. This provides availability of data in the event that a disaster should occur with the local UAS database.

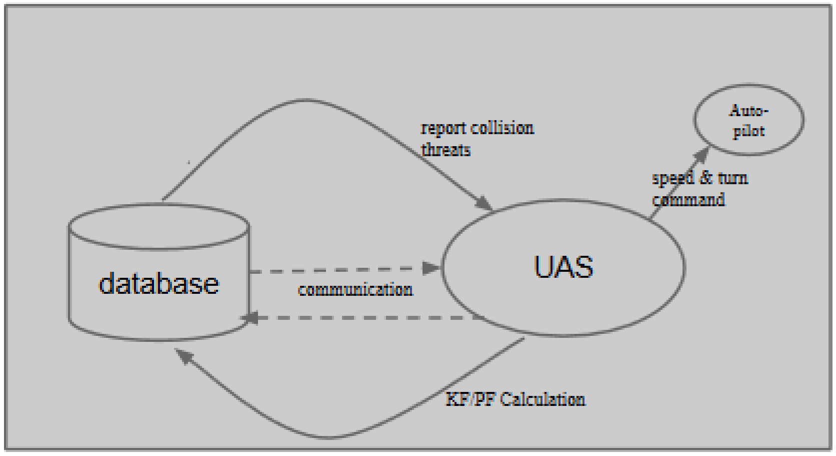

Figure 1: Accident Avoidance Systems for UAS

3.1 Filtering

Filtering is a frequently used method in engineering and embedded systems. A good filtering algorithm can reduce the noise from signals while retaining the useful information. The technique involves a process of computing the belief state – that is, the posterior distribution over the most recent state (X_t) - given all evidence (e) to date. In our example, we wish to compute P ($X_t|e_{1:t}$). In the UAS example, this would mean computing the probability of the current location, given all the observation of the aircraft position made so far. Figure 2 shows the probability of the UAS location [16].

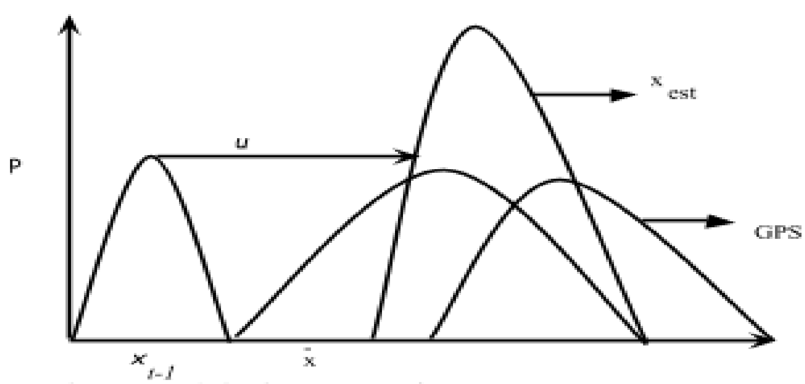

Figure 2: Graph showing movement of a UAS system

X_t: Represents the estimated location of the UAS at time *t*.
X_{t-1}: Represents past location of UAS at time *t-1*.
$e_{1:t}$: Represents the evidence of the UAS from time *1* to *t*.
e_{t+1}: Represents next evidence of the UAS at time *t+1*

3.1.1 Kalman Filtering

The kalman filter is an intelligent way to incorporate measurement data into an estimate. The algorithm used in conducting this study realizes that measurements are noisy and sometimes these measurements should be ignored or have only a diminutive effect on the state estimate. By incorporating more information from reliable data than from unreliable data, this technique smooths out the effects of noise in the state variable being estimated. Below is the algorithm that is incorporated in the study. The algorithm is adopted from Russel and Norvig [16].

$$P(X_{t+1}|e_{1:t+1}) = f(e_{t+1}, P(X_t|e_{1:t}))$$

Two steps are involved in the KF process: firstly, calculation for the current state distribution is done, that is, from *1* to *t+1;* secondly, the current state is updated using new evidence e_{t+1}.

$$\begin{aligned} P(X_{t+1} \mid e_{1:t+1}) &= P(X_{t+1} \mid e_{1:t}, e_{t+1}) && \text{(separating evidence)} \\ &= \alpha\, P(e_{t+1} \mid X_{t+1}, e_{1:t})\, P(X_{t+1} \mid e_{1:t}) && \text{(application of Bayes' rule)} \\ &= \alpha\, P(e_{t+1} \mid X_{t+1})\, P(X_{t+1} \mid e_{1:t}) && \text{(by the Markov sensor assumption).} \quad (1) \end{aligned}$$

α is a normalization constant used to ensure probabilities add up to 1. The second term, $P(X_{t+1} \mid e_{l:t})$ represents a one-step prediction of the next state, and the first term updates this with the new evidence. The one-step prediction for the next state is obtained by conditioning on the current state X_t:

$$\begin{aligned} P(X_{t+1} \mid e_{1:t+1}) &= \alpha\, P(e_{t+1} \mid X_{t+1}) \sum_{x_t} P(X_{t+1} \mid x_t, e_{1:t})\, P(x_t \mid e_{1:t}) \\ &= \alpha\, P(e_{t+1} \mid X_{t+1}) \sum_{x_t} P(X_{t+1} \mid x_t)\, P(x_t \mid e_{1:t}). \end{aligned} \qquad (2)$$

The filtered estimate $P(X_t \mid e_{l:t})$ is seen as a "message" $f_{l:t}$ that is propagated forward along the sequence, modified by each transition and updated by each new observation. The process is given by

$f_{1:t+1} = \alpha\, \text{FORWARD}(f_{1:t}, e_{t+1})$ where $f_{1:t} = P(X_t \mid e_{1:t})$ $f_{1:0} = P(X_0)$
Where FORWARD implements the update described in (2).

3.1.2 Particle Filtering

The particle filter is a collection of particles where each particle represents a potential current mean state of the UAS system. That is, it is a Monte Carlo simulation of data to get the estimates and can be quite effective in approximating when given enough samples [16]. Because the particle filtering uses random sampling, it does not share the same strict gaussian prerequisites as the Kalman filtering. There are many factors that can make a UAS system behave erratic. For instance, the region/environment in which the UAS is action in, and there could be other algorithms that is time dependent with exponential time function. By adding this non-linearity to the action command and data of the KF, strange distribution is produced that does not follow the linear rule of KF. With that being said, KF becomes obsolete, so we opt for particle filter. Particle filter consist of a series of steps; first, particles are sampled, samples are then weighted. Finally, values are resampled based upon the weighted values. The weights are based upon the probability of the given observation for a particle, given the actual observation.

Particle filtering works as follows: First, a population of *N* initial-state samples is created by sampling from the prior distribution P (X_o). That is, $N(x_t|e_{1:t}) / N = P(x_t|e_{1:t})$ Then the update cycle is repeated for each time step:

1. Each sample is propagated forward by sampling the next state value X_{t+1}:
$N(x_{t+1} \mid e_{1:t}) = \sum x_t \, P(x_{t+1} \mid x_t) \, N(x_t \mid e_{1:t})$ (3)

2. Each sample is weighted by the likelihood it assigns to the new evidence, P ($e_{t+1} \mid x_{t+1}$).
$W(x_{t+1} \mid e_{1:t+1}) = P(e_{t+1} \mid x_{t+1}) \, N(x_{t+1} \mid e_{1:t})$ (4)

3. The population is *resampled* to generate a new population of *N* samples proportional to *W*.

$N(x_{t+1} \mid e_{1:t+1}) / N = \alpha W(x_{t+1}|e_{1:t+1})$
$= \alpha P(e_{t+1}|x_{t+1}) \, N(x_{t+1}|e_{1:t})$
$= \alpha P(e_{t+1}|x_{t+1}) \sum x_t \, P(x_{t+1}|x_t) \, N(x_t|e_{1:t})$
$= \alpha P(e_{t+1}|x_{t+1}) \sum x_t \, P(x_{t+1}|x_t) \, P(x_t|e_{1:t})$
$= P(x_{t+1}|e_{1:t+1})$ (5)

3.2 Smoothing

We compute P ($X_k|e_{1:t}$) for some k such that $0 \leq k < t$. In the UAS example, it might mean computing the probability of the UAS position at some point in time, given all the observations of the UAS location made up to today. Smoothing gives a better estimated trajectory of the state than was available at the time, because it incorporates more evidence [16]. Computation is done in two phases- the evidence up to the past time *k* and the evidence from the past *k+1* to *t.*

$P(X_k|e_{1:t}) = P(X_t| e_{1:k}, e_{k+1:t})$: dividing up the evidence $e_{1:t}$ into $e_{1:k}$, $e_{k+1:t}$
$= \alpha P(X_k|e_{1:k}) P(e_{k+1:t}|X_k, e_{1:k})$: using Bayes' rule
$= \alpha P(X_k|e_{1:k}) P(e_{k+1:t}|X_k)$: using conditional independence
$= \alpha f_{1:k} b_{k+1:t}$. (6)

The forward message $f_{1:k}$ is computed by filtering forward from 1 to *k*, as depicted by equation (2). While the backward message $b_{k+1:t}$ is computed as $P(e_{k+1:t} \mid X_k)$

4 Results

In this section of the paper, we compare the results obtained by simulating the filtering cases with the ones obtained from the smoothing case. For this purpose algorithms are implemented in Matlab. A simple case was considered: A UAS that follows a path obtained for the system model. The figures that follow show, the estimated path of the UAS compared to the real path.

For the KF the simulation is done with the following parameters:
measured noise = 10; accelerated noise = 0.2; transitional matrix = [1 dt; 0 1]; input matrix = [dt^2/2; dt]; measurement matrix = [1 0]; initial state vector = [0; 0]; initial state estimate = initial state vector; measurement error covariance = measured noise^2; process noise covariance = accelerated noise^2* [dt^4/4 dt^3/2; dt^3/2 dt^2]; initial estimated covariance = process noise covariance

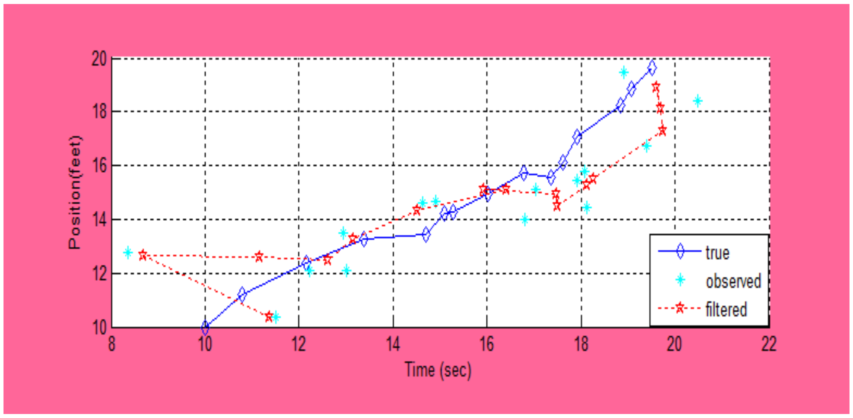

Figure 3: Position estimation with the Kalman filtering

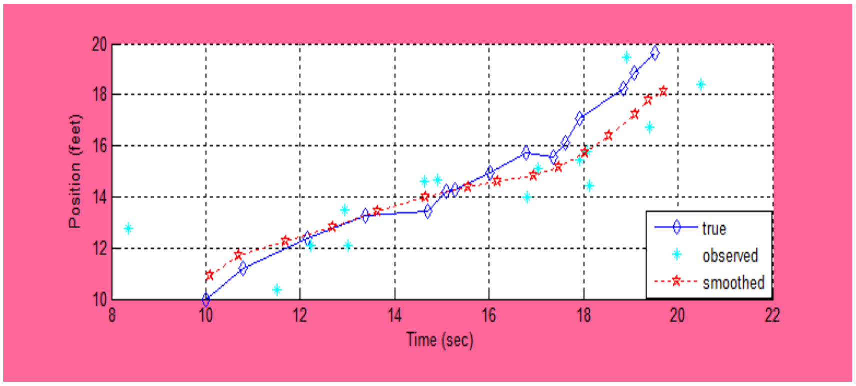

Figure 4: Position estimation with the Kalman smoothing

In fig. 3 and 4, the path estimation of the UAS is shown with the help of KF/KS. The blue line represents the location of the UAS (true position), the cyan represents the measured position (noisy), and the red line shows the tracking of the UAS using KF/KS.

For the PF the simulation is done with the following data:
Let the initial state = 1; process noise covariance = 1.0; measurement noise covariance =0.1; number of particle = 100;
The larger the number of particles/samples the better the computation but more computation is required.

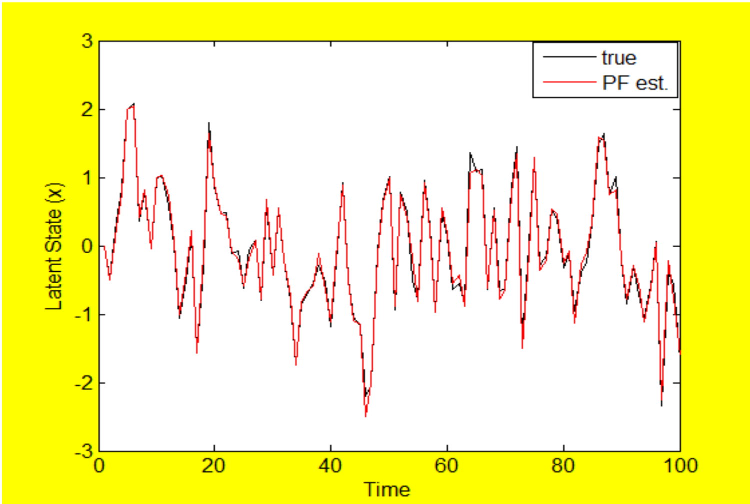

Figure 5: Position estimation using Particle filtering

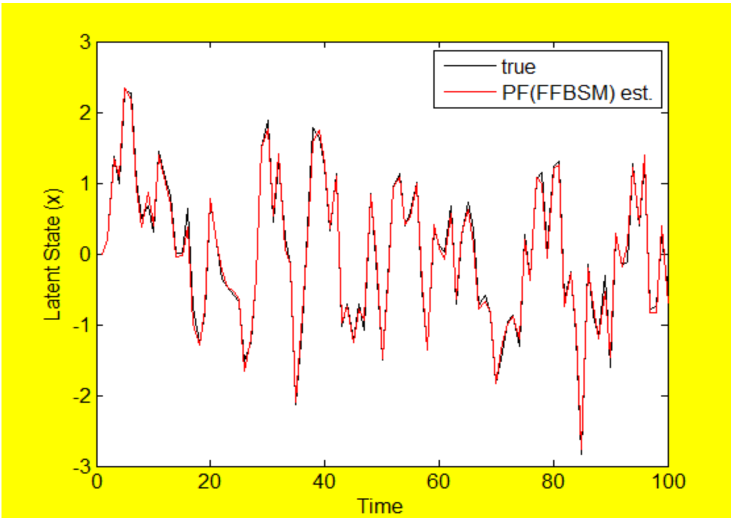

Figure 6: Position Estimation using Particle smoothing

5 Conclusion

One of the principal concerns with amalgamating unmanned aircraft into civil airspace is their lack of ability to robustly sense and avoid other aircraft. In order to overcome the shortcomings accurate localization is an essential requirement. Algorithms that perform well in tracking objects are Kalman filtering/smoothing and particle filtering/smoothing. Kalman filtering/smoothing is a linear system of equation and often performs well in tracking a linear system. However, it lacks the ability to perform when a problem is nonlinear or the noise that distorts the signal is non-gaussian. In such instance the particle filtering/smoothing is a more optimal solution.

The experimental result shows that irrespective of the errors in the measurements, both filters perform well in estimating the true position of the system. However, the smoothing techniques show the higher accuracy of the results due to the use of more future data than filtering technique. The mean squared estimation (mse) errors for Kalman filtering and smoothing are 5.0578 and 3.2473 respectively. While 0.10726 and 0.09147 are the calculated errors for Particle filtering and smoothing consequently.

These techniques can be applied to other autonomous systems to give an accurate and improved estimation based on a series of noisy estimates.

Acknowledgement

Conference presentation of this work has been partially sponsored under the University of North Dakota - Research Development and Compliance (RD&C), Division of Research. Funding is made available through a grant from the North Dakota EPSCoR Program, NSF grant #ESP-0814442. The UND Intercollegiate Academic also makes available Funding for the effort. Intercollegiate Academic Funding Award No. [60].

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