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Target Tracking Using Adaptive Marginalized Particle Filter

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ABSTRACT

Target tracking is an important element that is present in many applications in science including collision avoidance, surveillance, positioning, object detection, etc. Many scientists for decades have been developing new and new algorithms to solve problems related to target tracking. In general, the prime objective of any target tracking problem is to find/estimate the state variables of the associated system as fast as possible at the same time with minimum variance. Particle Filter is considered as the most standard method used to solve such problems. The curse of dimensionality has made scientists utilize the system properties and design some special estimation filters like Marginalized Particle Filter. The Marginalized Particle filter is not only free from the curse of dimensionality but is also faster than the standard Particle Filter. With the development of new technologies, the computational power has also improved but still, estimation speed is an important parameter when it comes to target tracking problems especially in application related to tracking missiles, enemy aircraft, etc. Adaptive Marginalized Particle Filter is an improved filter which yields estimates faster by utilizing the variable nature of the noise present in the system. In this paper, the performance of Adaptive Marginalized Particle Filter will be studied compared to Particle Filter and Marginalized Particle Filter by doing simulation using MATLAB by taking a target tracking application. Simulation datasets will be generated using a 2D constant acceleration model. From the simulation, it will be clearly understood that the Adaptive Marginalized Particle Filter is much better than the conventional filters in terms of estimation speed and variance of estimates.

Keywords: *Estimation, tracking, particle filter, marginalized particle filter*

1. INTRODUCTION

Target tracking is one of the many applications in science that has been fascinating to scientists for many decades. The idea of state estimation has marked a new era in solving such problems. Target tracking is considered a prime element when it comes to many applications in science such as collision avoidance, surveillance, positioning, object detection, etc. State estimation is an art of evaluating the variable of interest using a set of noisy, indirect measurements. In the case of a target tracking application, the variable of interest includes the states that represent a moving target.

A typical state estimation technique comprises of two models namely the state transition model and measurement model [1], [2], which will be used to represent the problem. The state transition model gives the relation between the various states associated with the system and how it varies with respect to time. Most of the time, a direct measurement of state variables may not possible due to constraints related to sensors, environment, etc. however the measurement of some indirect variables may be possible. Measurement model gives the relation between the measured data and the actual state variables describing the system.

In target tracking, the estimation technique can be considered effective if, it can find the estimates faster, with minimum variance, and track even in a highly noisy environment. The performance of state estimation techniques depends on several factors including, the credibility of the model (state transition and measurement models), noise levels of the measurements, etc. Emphasis should be given while selecting the model which will represent the problem as accurately as possible. No matter how much effort is given in designing the state estimation technique, if the model cannot accurately represent the problem then the overall performance of the estimation will be mediocre. In addition to the quality of the models, another important parameter is related to the ability of the state estimation technique in the retrieval of useful information from the noisy measurements.

There are a wide variety of state estimation filters which can be used to solve target tracking applications. The selection of filters is determined based on the characteristics of the model and the noise associated with it. Kalman Filter (KF) [3],[4] is considered to be the optimal state estimation technique due to its ability to find the estimates with minimum variance possible. KF is applicable only when the model has linear characteristics and the noises can be approximated to Gaussian. In such a situation no other filter can perform better than KF.

Practical tracking problems can be seldom considered to possess a linear model. Process model (State transition) and measurement model or either process model or measurement model may be nonlinear and hence in such a practical situation, KF cannot be utilized in the estimation process. To tactical solve such a situation several different versions of KF have been developed. Extended Kalman Filter (EKF) is a modified version of KF which can be applied in the case of nonlinear models. EKF achieve estimation using the concept of linearization. However, larger nonlinearities can lead to filter divergence. Unscented Kalman Filter (UKF), is another version of KF which can be used to solve target tracking problems and yield satisfactory performance whenever the nonlinearities are comparably small.

When Gaussian approximation, linearization techniques results in mediocre estimation performance, another category of state estimation technique such as Sequential Monte Carlo methods (SMC) also known as Particle Filter (PF) [5], [6] are made use of. In PF, state estimation is achieved by evaluating aposterior probability density function (pdf) at each stage and propagating whenever a new measurement data comes.

In the case of PF, the aposterior distribution is represented using a set of a weighted samples known as particles. Here the weight associated with each particle is a clear indication of the quality of the data that is been represented by the particle, i.e if the weight is zero then the information represented by that particle will be of no use when compared to a particle with a certain weight. The accuracy of the representation of the aposterior distribution depends on the number of particles used to represent the distribution, more the number of particles, better the representation. The curse of dimensionality is the major drawback when it comes to PF, which is nothing but, more the number of particles more will be the computation complexity of PF which will increase drastically depending on the dimension of that state variables.

Thus, PF will be an effective state estimation technique for solving the target tracking problem when the dimension of the state variables is less. PF can be considered as the general filter that can be applied to any problems with linear or nonlinear models and with any type of noise. There is another problem that affects the estimation process, namely degeneracy. Degeneracy can be thought of as a situation in which after few iterations the weight of some of the particles will reduce to zero thereby making them ineffective in the estimation process. If this problem is not addressed, it can lead to filter divergence. A computationally complex technique known as Resampling [7]–[9] can be incorporated along with PF to solve the problem of degeneracy. But this will further increase the computational complexity of the PF. If some relaxation can be given to noise affecting the system, which can be approximated to Gaussian, then a modified version known as Gaussian Particle Filter (GPF) [10], [11] can be used. GPF yields performance similar to that of PF but with lesser computation complexity being limited to Gaussian Noise.

As mentioned in the starting section of the paper, representation of the system using an appropriate system and measurement model is a very important step in solving target tracking problems using state estimation techniques. Upon studying the models that are generally associated with problems related to target tracking, it can be brought to the notice that in most situations, the model associated with the problem is characterized by a linear system model, nonlinear measurement model and the noise associated with the system will be Gaussian. This allowed scientists to develop a new class of estimation filter specially designed for problems [12]–[14] having models with linear Gaussian substructure.

Marginalized Particle Filter (MPF) [15]–[17] has been developed to solve models with linear Gaussian substructure in which the state variables will be marginalized out into two state vectors. One state vector constitutes the linear state variables and other nonlinear state variables. Once marginalization is done, the linear state variables will be estimated using KF, and the estimation of nonlinear state variables will be carried out using PF. The main advantage of such type of approach is that the dimension of state variables which is estimated using PF will be reduced and hence the overall computational complexity decreases and hence estimation of states using MPF can be achieved much faster than using standard Particle Filter and results in estimates with lesser variance [18], [19].

The state estimation techniques discussed so far depends on the type of system model. Noise affecting the measurements is another important parameter that affects the performance of the estimation process. In Science, noise is considered random which means its occurrence cannot be deterministically mentioned. Thus, in practical scenarios, the amount of noise affecting the measurement data will keep on varying, at times having less value and at other times having larger value. MPF and PF are designed to operate with a constant number of particles without considering the amount of noise affecting the measurements. As MPF is much better than PF and can withstand noise much better as discussed and explained in [18], a new type of state estimation filter by taking into consideration this varying nature of the noise known as Adaptive Marginalized Particle Filter (AMPF) [20] is developed.

Adaptive Marginalized Particle Filter is an improved version of MPF which adapts the number of particles depending upon the amount of noise affecting the measurement data. AMPF being an improved version of MPF obtain estimates much faster and even better variance at times. Similar to MPF, in AMPF also linear state variables will be estimated using KF and nonlinear state variables will be estimated using PF. The basic idea and formulation of AMPF will be briefed in the upcoming sections. This paper is written to demonstrate how Adaptive Marginalized Particle Filter can be applied in the case of a typical target tracking problem. All the simulation is done using MATLAB running in 8GB Ram, i7 Intel Processor computer. From the simulation, it will be clear the performance excellence of AMPF compared to MPF and PF in terms of Root Mean Square Error (RMSE) and execution speed.

Section 2 gives the details of the important special class of model that is commonly found in applications such as collision avoidance, target tracking, positioning, surveillance, object detection, etc. AMPF algorithm employed for target tracking applications is discussed in Section 3. Section 4 gives the typical target tracking example used for the simulation and the results are mentioned in Section 5. Finally, the conclusion and remarks are discussed in Section 6.

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2. IMPORTANT SPECIAL DYNAMIC STATE SPACE MODEL

The special class of dynamic state space model which is commonly utilized in the case of target tracking applications consists of linear state equations and measurement equations are of a nonlinear type. This will be clear by investigating the general and important special class model equations.

The general model [15] is given in Equation 1.

$$x_{t+1}^n = f_t^n(x_t^n) + A_t^n(x_t^n)x_t^l + G_t^n(x_t^n)v_t^n \tag{1a}$$

$$x_{t+1}^l = f_t^l(x_t^n) + A_t^l(x_t^n)x_t^l + G_t^l(x_t^n)v_t^l \tag{1b}$$

$$y_t = h_t(x_t^n) + C_t(x_t^n)x_t^l + e_t \tag{1c}$$

$x_{t+1}^n, x_{t+1}^l, x_t^n, x_t^l$ represents the nonlinear and linear state variables at $(t+1)^{th}$ and t^{th} time. y_t gives the t^{th} time interval measurements. $G_t^n(x_t^n), G_t^l(x_t^n), C_t(x_t^n), A_t^l(x_t^n)$, $A_t^n(x_t^n)$ describes the constant matrix functions. $h_t(x_t^n)$ gives the measurement function and $f_t^n(x_t^n), f_t^l(x_t^n)$ represents the functions related to nonlinear and linear state variables. The process and measurement noise are represented by v_t and e_t respectively. The noises are assumed to be Gaussian.

The important special model [18], [20], [21], [15] is represented using Equations 2.

$$x_{t+1}^n = A_{n,t}^n x_t^n + A_{l,t}^n x_t^l + G_t^n v_t^n \tag{2a}$$

$$x_{t+1}^l = A_{n,t}^l x_t^n + A_{l,t}^l x_t^l + G_t^l v_t^l \tag{2b}$$

$$y_t = h_t(x_t^n) + \qquad + e_t \tag{2c}$$

$A_{n,t}^n, A_{n,t}^l, A_{l,t}^n, A_{l,t}^l, G_t^n, G_t^l$ represents the constant matrices related to nonlinear and linear state variables. On comparing equations 1 & 2 it is clear that the state equations are linear and the measurement equation is nonlinear. Also, it is worth noting that the measurement equation (2c) contains only nonlinear information and hence the measurement data can be only used in the case of particle filter during the estimation process. The effect of measurement reaches KF via the time update and not through the measurement update.

3. ADAPTIVE MARGINALIZED PARTICLE FILTER

Adaptive Marginalized Particle Filter [20], [21] is an improved/modified version of the Marginalized Particle Filter designed to utilize the varying nature of noise affecting the measurement data. It has been already proved the noise tolerance property of MPF. The conclusion that can be drawn from this property is that even if the number of particles used to represent the distribution is reduced the effect it produces on the variance of the estimates will be less when compared to that produced in the case of PF. AMPF is based on this noise tolerance property of MPF. The basic idea behind AMPF is to adapt the number of particles depending upon the amount of noise present in the measurements.

Thus, AMPF makes use of these fluctuating characteristics of noise thereby reducing the number of particles whenever the noise is less and resetting to the normal number of particles when the noise is more. As the number of particles is reduced whenever possible by accounting the amount of noise present in the measurement the overall estimation speed will be improved even when compared to that obtained in the case of MPF. It is also worth noting that whenever the number of particles is reduced the aposterior distribution will be reinitialized.

The main improvement that can be seen when estimation is done using AMPF is twofold, the estimation speed will be improved and due to the reinitialization of aposterior distribution, the variance of the estimates will be much less when the amount of noise affecting the measurements are more. Similarly, the improvement seen in terms of execution speed will be more when the fluctuation of noise is more.

The detailed algorithm along with the various steps involved in the Adaptive Marginalized Particle Filter is mentioned in the following papers [20], [21].

4. TARGET TRACKING PROBLEM AND SIMULATION

A target tracking problem [18], [20], [21], [19], [22] is considered in this paper in order to evaluate the performance of Adaptive Marginalized Particle Filter. The problem includes the tracking of an aircraft performing some maneuvering. The various variables of interest including position and velocity will be estimated using the state estimation technique AMPF. The problem will be modeled as a 2-dimensional constant acceleration model. A level flight is considered to make the problem less complicated. The dynamic state-space model of the problem considered is mentioned in Equation 3 where the height component is discarded as the aircraft is assumed to possess a level flight.

$$x_{t+1} = \begin{bmatrix} 1 & 0 & T & 0 & \frac{T^2}{2} & 0 \\ 0 & 1 & 0 & T & 0 & \frac{T^2}{2} \\ 0 & 0 & 1 & 0 & T & 0 \\ 0 & 0 & 0 & 1 & 0 & T \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} x_t + v_t \tag{3a}$$

$$y_t = \begin{pmatrix} r \\ \theta \end{pmatrix} = \begin{pmatrix} \sqrt{p_x^2 + p_y^2} \\ \arctan(p_x / p_y) \end{pmatrix} + e_t \tag{3b}$$

Equations (3a) & (3b) denotes the state equation and measurement equation respectively. On comparing with the important special class model mentioned in section 2, it is clear that the above tracking problem belongs to that category in which the state equations are linear and measurement equations are nonlinear.

In this problem, the range and bearing angle of aircraft are the measurement data which will be used by AMPF to estimate the state variables including position, velocity, and acceleration. $p_x, p_y, v_x, v_y, a_x, a_y$ represents the position, velocity, and acceleration state variables along x and y coordinates. The z coordinate is not considered due to the level flight assumption made earlier. $\boldsymbol{x}_t = (p_x, p_y, v_x, v_y, a_x, a_y)^{\mathrm{T}}$ represents the state vector comprising of the state variables. T gives the sampling period which is assumed to be 1 sec. Measurements range and bearing angle are denoted by r and θ. $\boldsymbol{e}_t$ and $\boldsymbol{v}_t$ represents the measurement and process noises associated with the model having covariance

$$\boldsymbol{R} = \operatorname{cov} \boldsymbol{e} = diag\left(250, 0.5\right) \tag{4a}$$

and

$$\boldsymbol{Q}^n = cov\left(\boldsymbol{v}^n\right) = diag(450, 450) \tag{4b}$$

$$\boldsymbol{Q}^l = cov\left(\boldsymbol{v}^l\right) = diag(5, 4, 0.8, 0.7) \tag{4c}$$

respectively.

The state vector comprises of position, velocity, and acceleration components, in which position components constitute the nonlinear state variables, velocity, and acceleration components constitute the linear state variables. Therefore, the state vector can be split into two as follows

$$\boldsymbol{x}_t^n = \begin{bmatrix} p_x \\ p_y \end{bmatrix}, \boldsymbol{x}_t^l = \begin{bmatrix} v_x \\ v_y \\ a_x \\ a_y \end{bmatrix} \tag{5}$$

where $\boldsymbol{x}_t^n, \boldsymbol{x}_t^l$ denotes the nonlinear and linear state variables respectively. On comparing the dynamic state-space model of the problem with the given important special model it can be noted that the value of the term $\boldsymbol{A}_{n,t}^l \boldsymbol{x}_t^n$ is zero and the corresponding terms are given by

$$\boldsymbol{G}_t^n = \boldsymbol{I}_{2X2}; \boldsymbol{G}_t^l = \boldsymbol{I}_{4X4}$$

$$\boldsymbol{A}_{n,t}^n = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}; \boldsymbol{A}_{l,t}^n = \begin{pmatrix} 1 & 0 & 0.5 & 0 \\ 0 & 1 & 0 & 0.5 \end{pmatrix}$$

$$\boldsymbol{A}_{n,t}^l = \boldsymbol{0}_{4X2}; \boldsymbol{A}_{l,t}^l = \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{6}$$

The state estimates of the target tracking problem are evaluated using Monte Carlo (MC) simulations. 200 MC simulations are done to get a stable estimate. The experimental data used for simulation is first evaluated using equations 3. The actual values of state variables will be used as a reference to determine the performance of AMPF by comparing the evaluated state estimate with the original values of the state variables. The measurements range, and bearing angle is also calculated using the original state variables and are contaminated with Gaussian noise before giving to the AMPF for state estimation to make the simulation closer to the real-world scenario.

The measurements are also given to MPF and PF for state estimation of the performance all the three filters will be compared. One way of performance comparison is based on Root Mean Square Error (RMSE) which is the most popular parameter and it is defined as

$$\left(\frac{1}{\mathrm{N}} \sum_{t=1}^{N} (1/N_{MC}) \sum_{j=1}^{N_{MC}} \left\| \boldsymbol{x}_t^{true} - \hat{\boldsymbol{x}}_t^{(j)} \right\|_2^2 \right)^{1/2} \tag{7}$$

where $\boldsymbol{x}_t^{true}$ and $\hat{\boldsymbol{x}}_t^{(j)}$ denotes the original value and the estimated value of the state variable at time t of j^{th} MC simulation. N_{MC} gives the number of Monte Carlo simulations and N gives the number of times samples. The filter parameters used for MC simulation are given in Table 1.

Resampling which is done to avoid the problem of degeneracy is also a deciding factor of the performance of the AMPF filter. The effect of different resampling techniques is discussed in the paper [21].

The aircraft trajectory used for the simulation is illustrated in Figure 1 and simulation is carried out using 5000 particles for 200 MC simulations. Now onwards execution time will be expressed in seconds (s), RMSE related to velocity and position will be expressed in m/s and m respectively. The initial coordinates of the aircraft are assumed to be at the coordinates [-1000*10, 1000*5], observer (Radar) is located at the origin of the coordinate system, and aircraft moves with a constant acceleration of 0.5 m/s^2.

Figure 1 shows the actual trajectory the aircraft takes comprising of turns and straight-line motion. As mentioned, earlier all the values of the state variables position, velocity, acceleration, range and bearing angle corresponding to this

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aircraft trajectory will be evaluated using Equation 3 for 600-time samples and will be stored as reference for comparing

TABLE I. PARAMETER VALUES

Parameter	Values
Number of Monte Carlo Simulations	200
Initial Position $[p_x, p_y]$ in m	[-1000*10,1000*5]
Initial Velocity $[v_x, v_y]$ in m/s	40
Acceleration $[a_x, a_y]$ in m/s^2	0.5
Initial state covariance $\boldsymbol{P_o}$	diag(0.02,0.02,0.02, 0.02,0.02,0.02)
Measurement Noise Covariance $\boldsymbol{R}$	diag(250,0.5)
Non-linear Process Noise Covariance $\boldsymbol{Q^n}$	diag(450,450)
Linear Process Noise Covariance $\boldsymbol{Q^l}$	diag(5,4,0.8,0.7)

the performance of the state estimation using PF, MPF, and AMPF. The range and bearing angle of the aircraft with respect to the observer serves as the input to all the filters. The precalculated range and bearing angle will be contaminated

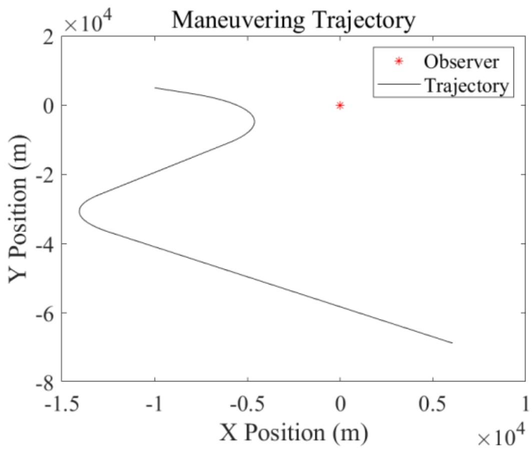

Figure.1. Maneuvering trajectory traced by the aircraft with initial coordinates [-1000*10, 1000*5] and * denotes the location of the observer.

with Gaussian noise before it is applied to the filters. The corresponding range and bearing angle are shown in Figure 2 (a) & (b) respectively.

The performance of the state estimation filters applied to this target tracking example will be discussed in section 5.

5. RESULTS AND DISCUSSION

The effectiveness of any state estimation filters as those mentioned in this paper is usually expressed in terms of variance of the estimates and execution time. The variance of the state estimates which is an indication of the deviation from the reference values must be as small as possible showing better tracking.

Figure 3 shows the tracking of the trajectory by PF, MPF,

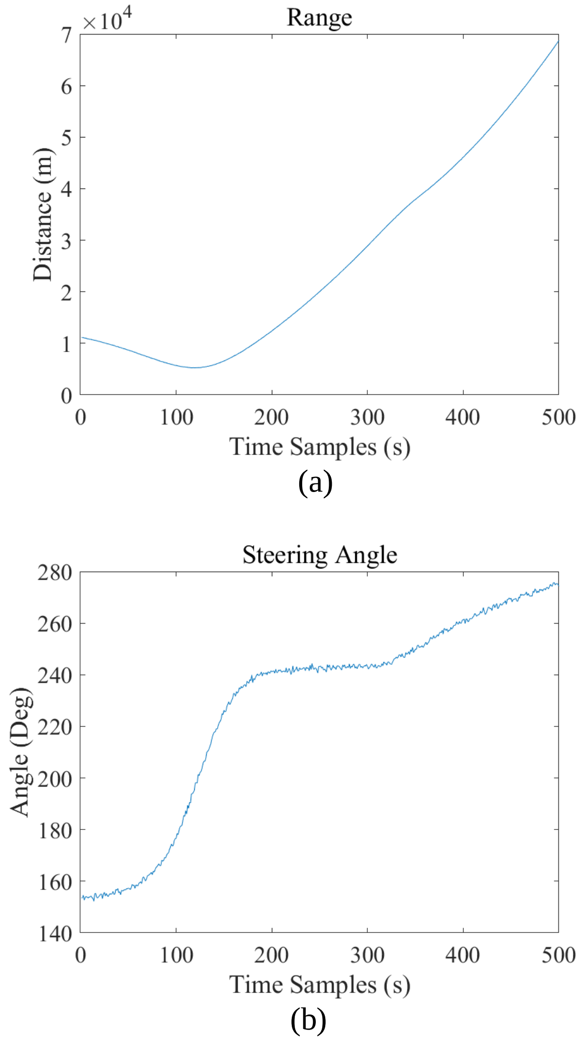

Figure.2. Range and Bearing Angle. (a) Range (m) (b) Bearing Angle (deg)

AMPF. From the figure it is clear that all the three filters are able to track the trajectory, however the estimates obtained using AMPF has less variance which will be clear by comparing the overall RMSE of state variables given in Table II.

TABLE II. SIMULATION RESULT OF PF, MPF & AMPF IN THE CASE OF MANEUVERING TRAJECTORY WITH 5000 PARTICLES

Parameter	PF	MPF	AMPF
Execution Time	0.75108	0.72756	0.44266
RMSE X Position	136.20087	128.2502	125.52308
RMSE Y Position	177.8566	163.9899	160.66835
RMSE X Velocity	12.24920	10.72792	10.19292
RMSE Y Velocity	14.63040	12.97513	12.6135

From Table II, it can be noted that the Root Mean Square Error (decimal values not mentioned) of the x coordinate of position is 136 m in the case of PF, 128 m with MPF, and 125 m in the case of AMPF. It can be interpreted that AMPF was able to estimate the x position state variable with lesser variance than with PF and MPF. This is a clear indication that AMPF can

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track the aircraft much better than the other two filters. A similar result is observed in the case of the y coordinate of position as well. RMSE along y position is 177 m with PF, 163 m in the case of MPF, and only 160 m using AMPF. Here also it can be concluded that AMPF outperforms other filters. State variable velocity along x and y coordinates is also estimated using the three filters. It can be comprehended from Table II

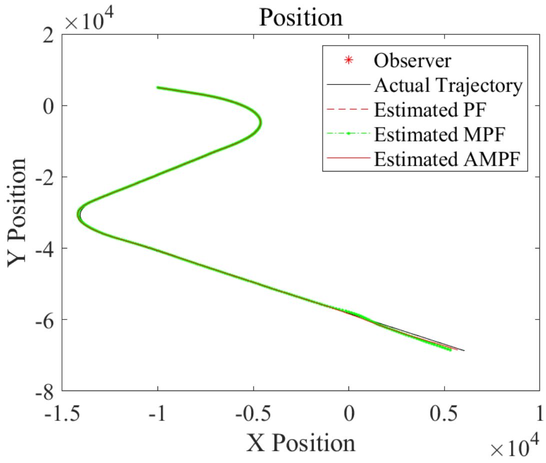

Figure.3. Tracking of Manuvering Trajectory by PF, MPF & AMPF

that the velocity estimates obtained using AMPF are much better than those obtained using MPF and PF. These results are in line with the results obtained in paper [20] where AMPF is applied in the case of a Non-Maneuvering and a different Maneuvering Trajectory.

The main feature of AMPF, when compared to MPF and PF is its execution speed. From Table II, it is evident that AMPF can find the state estimates much faster than that obtained using MPF and PF. PF took nearly 0.75108s for estimation to complete while MPF needed only 0.72756s but AMPF was even faster than the two, taking only 0.44266s to complete the estimation process. Thus, an improvement of 41 % and 39 % with respect to PF and MPF is obtained.

TABLE III. SIMULATION RESULT OF PF, MPF & AMPF IN THE CASE OF MANEUVERING TRAJECTORY WITH 10000 PARTICLES

Parameter	PF	MPF	AMPF
Execution Time	1.39615	1.26689	0.75055
RMSE X Position	137.72451	129.44478	126.63331
RMSE Y Position	172.5083	165.1298	162.1706
RMSE X Velocity	12.71626	10.69317	10.0143
RMSE Y Velocity	13.88465	12.43446	12.0547

It can also note that as the number of particles is increased then the improvement in execution time is similar to that obtained using a lesser number of particles indicating the consistency and the variance is also less compared to MPF & PF. This can be clearly understood by comparing the results given in Table II & III. The main reason for the improvement in variance even though the number of particles is reduced is mainly due to the reinitialization step of AMPF algorithm [20], [21].

Thus, from Figure 3 and tables II & III, it can be concluded that target tracking using the state estimation filter AMPF will yield much better performance compared to that obtained in the case of PF and MPF in terms of RMSE and execution time.

6. CONCLUSION

The solution for target tracking applications by one of the finest state estimation algorithms Adaptive Marginalized Particle Filter and the improvement obtained by the filter compared to the conventional filters like Particle Filter and Marginalized Particle Filter is studied. The effect of the reinitialization step of AMPF on the performance was demonstrated by the simulation using a typical target tracking example. The improvement in execution time will be a big bonus when it comes to applications such as enemy target tracking, ballistic missile tracking, etc. as in such applications the faster the state variables can be found the sooner it can be intercepted. The AMPF algorithm can be also easily extended to the tracking of multiple targets.

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