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EFFICENT USE OF PARTICLE FILTER TO MEASURE THE MEASUREMENT AMBIGUITY PROBLEM IN INDOOR SPACE

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ABSTRACT

Particle filter (pf) method is thebest technique for indoor localization estimation and object tracing in smart building by the assistance of active or passive RFID reader and tags and Wi-Fi far more devices are used. Which can be accustomed gather indoor user position and the densityare calculated particle filter algorithm. The most use of Pf is employed used to estimate the nonlinear vector space Here the particle are going to be measure the particle densityambiguously. Once the item is measure on a 1 vector state then it store after moves the identical object to different one vector state, it'll store and update will make some trouble this trouble is overcome by using Sequential important sampling method (SIS).Here this paper is implement supported on sequence sampling dimension problem on this paper is updating measurement of the particle filter with resampling method. At just one occasiondetect an ambiguous dimension update is detected, the proposed method flights the measurement update at the time step and feats the measurement later when the particle distribution becomes tolerable for the dimension inform. This plan delivers a preparation to the paradox problem to get the correct current position estimate with lower covariance. Numerical imitation is presented to prove effectiveness and routine of the proposed method. Compared to other methods, like the quality particle filter, the auxiliary particle filter, the mixture particle filter, and also the receding-horizon Kalman filter, the proposed method shows better performance in terms of root-mean-square error and projected covariance. Here we define the unclear measurement update that results in increase in covariance and weight of the particles. The unknown measurement update causes larger dispersal of particles and provides a less assured approximation. So we are able to use the particle filter method in this work to get essential result instead of kalmanfilter (Kf). Kf is generally utilized in linear indoor vector space to estimate the article.

INTRODUCTION

The development of data formed via IoT has played a key role on the big data landscape. Big data can be categorized affording to three aspects: (a) volume, (b) variety, and (c) velocity. These types were first introduced by Gartner to define the essentials of big data contestshuge occasions are accessible by the skill to analyse and exploit huge amounts of IoT data, including applications in smart cities, smart transport and network systems, energy smart meters, and remote patient healthcare monitoring devices. IoT has made big data analytics stimulating because of the dispensation and collection of data through different sensors in the IoT environmentIoT offers a platform for sensors and devices to connect flawlessly within a smart environment and enables information sharing across platforms in a expedient manner. The current variation of different wireless technologies places IoT as the next radical technology by promoting from the full opportunities offered by the Internet technology. IoT has saw its recent acceptance in smart cities with interest in developing smart systems, such as smart office, smart retail, smart agriculture, smart water, smart transportation, smart healthcare, and smart energy.

In big data technique collect the data from different communication media like our day to day using devices.Severalkind of unstructured data. Those areconverting the structure data. The conversion data are store in a data storage pool the store data called by using some query and do some tasks.

Uses of particle filter

Its improved presentation in extremely nonlinear situation and aptitude to resolve a given global localization problem with no gen about the primary position.Particle filter is algorithmically more translucent and meet than extendedkalman filter. It is robust against modelling and computational error.

Particle filter has some problem associated with loss of multiplicity among the samples ensuing in failures of state estimate and large approximation errors.in propose limited impulse response filter detects the particle failure and recovers the failed particle filter by rearranging the particle filter using the output of an auxiliary fixed impulse response in the Angle of arrived signal.

PROBLEM DESCRIPTION

A. Bayesian Approximation

Images of nonlinear Bayesian approximation can be pledge in many works. A nonlinear stochastic scheme can be articulated by a discrete-time of approximation procedure model

$$xt + 1 = ft(xt, wt) \qquad (1)$$

And a measurement new model

$$zt = ht(xt, vt) \text{ (2)}$$

Where xt is mention system state trajectory and zt is the newly measurement trajectory at time lengthmentionast. The deterministic purposes and narrate the preceding state to the present state and the existing state to the dimension vector, respectively. wt is the process noise trajectory and VT is the measurement noise trajectory

Here the Bayesian estimation probability problem function density is denoteas$p(xt|z1{:}\,t)$. The prior density of the state at time k via the Chapman–Kolmogorov equation is shown below

$$p(xt|z1{:}\,x-1) = \square\; p(xt-1|z1{:}\,t-1)dxt-1 \quad (3)$$

Here $p(xt-1||z1{:}\,t-1)$is the previous objectdensity, by a dimensiontimezt, the inform phase is to get the later thickness via Bayes' rule

$$p(xt|z1{:}\,t) = \frac{p(zt|xt)p(xt|z1{:}t-1)}{p(zt|z1{:}t-1)} \quad (4)$$

From all the input data we could normalized the necessary data

$$p(zt|z1{:}\,k-1) = \int p(zt|xt)p(xt|z1{:}\,k-1)dxt(5)$$

The recursive proliferation of the advanced bulk is anintangible solution, which cannot be strong-minded logically. One can action the PF to fairly precise the optimal Bayesian solution.

B. Particle Filter

This paper give elaborate design is to the particle filtering algorithm with sequential importance resampling (SIR). The SIR is usually used in particle filtering algorithms used to resample the particle filter.

The subsequent probability is denoted by a set of haphazardly chosen weighted particles as

$$p(xt|z1{:}\,t) \approx \sum_{i=1}^{N} \omega_t^i \square(x^t - x_t^i) \quad (6)$$

Here δ represents the Dirac delta function, N mention the number of particles, ω_t^iestimate the importance weight of the ith particle, x_t^i mention the state of the jth particle, and $z1{:}\,t$ mention a set of measurements obtained until time t. here mention the pseudo code of SIR algorithm is described in given below algorithm1. The particles are drawn by the analytical conditional transition density $p(xt|xt-1)$ and the resultant particles of the estimate step are shows as $\tilde{x}_t^i$ for i=1……..N.

Algorithm 1: Resampling Particle Filter

1: Procedure RPF$\left(\{x_{t-1}^i\}_{i=1,}^N z_t\right)$

2: for i=1 : n do

3: Draw $\tilde{x}_t^i \sim p(xt|x_{t-1}^i)$

4: Calculate $\tilde{\omega}_t^i = (xt|\tilde{x}_t^i)$

5 Calculate sum of particle weights $\omega_{sum} = \square_{j=1}^{N} \tilde{\omega}_t^j$

6: for i =1 : N do

7: Normalize $\omega_t^i = \frac{\tilde{\omega}_t^i}{\omega_{sum}}$

8: Calculate CDF P using $\{\omega_t^i\}_{i-1}^N$

9: for i = 1 : N do

10: $u \sim U(0,1)$

11: $j = P^{-1}$(u)

12: $x_t^i = \tilde{x}_t^j$

Each particle sample can be drive from$p(x_t|x_{t-1})$ by developing a process noise sample $\omega_{t-1}^i \sim p(\omega_{t-1})$and setting

$\tilde{x}_t^i = ft(x_{t-1,}^i \omega_{t-1}^i)$Where $P(\omega_{t-1})$means the likelihood mass function ofω_{t-1}. Their weights are updated by using the view function$p(zt|xt)$, which is a predefined dispersal of the dimension given the preceding state. Later normalizing the position weights, the SIR PF calculates the collective distribution function (CDF) of the weights and resamples the particles founded on the CDF. $p-1$Means the opposite function of the CDF p by which the rearranged index $j$is got based on the random number u drawn from the uniform distribution$U(0,1)$. After the resampling, the resultant particles have identical weights as$\omega_k^i = 1/N,$ for i = 1, ..., N. The prior particles$\{x_{t-1}^i\}_{i=1}^N$ and the later particles $\{x_{t-1}^i\}_{i=1}^N$are used to calculate the state approximation and its covariance as

$$\hat{x}_t^- = \frac{1}{N}\sum_{i=1}^{N} \tilde{x}_t^i \, \hat{C}_t^- = \frac{1}{N}\sum_{i=1}^{N} (\tilde{x}_t^i - \hat{x}_t^-)(\tilde{x}_t^i - \hat{x}_t^-)^T \hat{x}_t^+$$

$$= \frac{1}{N}\sum_{i=1}^{N} \tilde{x}_t^i \, \hat{C}_t^+ = \frac{1}{N}\sum_{i=1}^{N} (\tilde{x}_t^i - \hat{x}_t^+)(\tilde{x}_t^i - \hat{x}_t^+)^T \quad (7)$$

Where the superscripts “–” and “+” denote estimates gained by the prior and the posterior particles, correspondingly.

C. Ambiguous Measurement Update

Surge in the particle covariance after the dimension update phase is often observed when there exist ambiguous points where the estimated capacities are identical to the measurement taken at the true state. This phenomenon usually happens around modulation points of the nonlinear function$h(x_t)$, where the sign of the gradient of the function changes.

Since the function value near an inflection point has its identical foil on the opposite side, the measurement update may result in a discrete posterior distribution for some cases.

Here, we describe the ambiguous measurement update as the measurement update that leads to surge in covariance of the particles. The ambiguous measurement update producing larger dispersal of particles provides a less confident estimate and it may cause chaining effect on subsequent steps of the recursive filter. In the next section, we provide a strategy to cope with the problem.

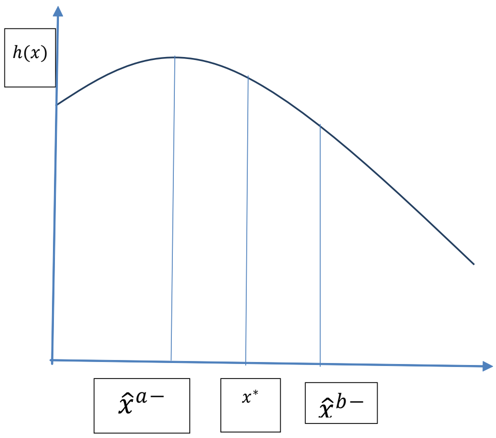

Fig. 1. One-step filtering with different prior distributions

PROPOSED ALGORITHM

As talked in Section II, an ambiguous measurement update results in a scatter posterior distribution with a less self-assured position estimate. The objective of the proposed algorithm is to get more confidence of the current estimate when an ambiguous measurement update happens and therefore realize better filter performance.

Algorithm 1: Sequential importance Resampling Particle Filter (SIR)

1: Procedure SIR$\left(\{x_{t-1}^{i}\}_{i=1,}^{N} z_t\right)$

2: for i=1 : n do

3: Draw $\tilde{x}_t^i \sim p(xt|x_{t-1}^i)$

4: Calculate $\tilde{\omega}_{t*}^i = (xt|\tilde{x}_t^i\ )$

5 Calculate sum of particle weights $\omega_{sum}\ =\ \square_{j=1}^{N}\tilde{\omega}_t^j$

6: for i =1 : N do

7: Normalize $\omega_{t*}^i = \frac{\tilde{\omega}_t^i}{\omega_{sum}}$

8: Calculate CDF P using $\{\omega_{t*}^i\}_{i-1}^{N}$

9: for i = 1 : N do

10: $u \sim U(0,1)$

11: $j = P^{-1}$(u)

12: $x_{t*}^{i} = \tilde{x}_{t}^{j}$

Algorithm 3: Proposed Algorithm.

fori =1 : N do

Initialize x_0^i~p(x_0)

For k = 1 : K do

[{ $x_t^i\}_{i=1}^{N}$,{$\tilde{x}_t^i\}_{i=1}^{N}$,{$\tilde{\omega}_t^i\}_{i=1}^{N}$]= SIR{ $x_{t-1}^i\}_{i=1}^{N}$,z_t

if $|\tilde{C}_t^+| < |\tilde{C}_t^-|$ then

if A≠ Ø then

for∀z_a Є A do

[{ $x_{t*}^i\}_{i=1}^{N}$,{$\tilde{\omega}_{t*}^i\}_{i=1}^{N}$] = XYZ ({$x_s^i\}_{i=1}^{N}$,{ $x_t^i\}_{i=1}^{N}$,{$\tilde{\omega}_t^i\}_{i=1}^{N}$, z_a)

if $|\tilde{C}_{t*}^+| < |\tilde{C}_t^+|$ then

{ $x_t^i\}_{i=1}^{N}$,= { $x_{t*}^i\}_{i=1}^{N}$,{$\tilde{\omega}_t^i\}_{i=1}^{N}$ = {$\tilde{\omega}_{t*}^i\}_{i=1}^{N}$

A≠ Ø

{$x_s^i\}_{i=1}^{N}$, = { $x_t^i\}_{i=1}^{N}$

Else

{ $x_t^i\}_{i=1}^{N}$ = {$\tilde{x}_t^i\}_{i=1}^{N}$

Insert z_k into A

The proposed algorithm requires extra computation associated to the standard PF to deal with the ambiguous measurement update. As described in Algorithm 3, determination of the ambiguous measurement update is done by comparing magnitude of the prior and posterior density. The later covariance can be attained after a measurement update, including a resampling stage, and any ambiguous measurement is used again later as an XYZ. Therefore, the proposed algorithm is supposed to execute one more measurement update stage per an ambiguous measurement

B. Other Filtering Techniques

In demonstrating the effectiveness of the proposed algorithm, it is worth to compare the filter behaviour to those of other filtering methods which may provide similar results: the auxiliary particle filter (APF), theMixture MPF, and the receding-horizon Kalman filter (RHKF).

1) Auxiliary Particle Filer:

The auxiliary particle filter is mainly used for resampling technique, which is used to provide the accurate soluction from the failure particle.was introduced in as a variant of the standard SIR filter. The auxiliary particle filter is mainly introduce the purpose of avoid the particle failure and error state estimation.

2) Mixture Particle Filter:

The MPF was proposed for dealing with multimodal distribution in particle filtering in global localization problems.it contain mainly used for large area estimated. The MPX algorithm is used to produce the particle on each state for estimate the covariance value. Each particle cluster is given a mixture weight and the cluster is maintained and updated by clustering algorithm such as the mean-shift clustering technique. The resampling techniques is used to estimate the error particle based on the particle weights and the mixture weights the MPF is compare with particle filter its take some amount of time for calculation.

3) Receding-Horizon Kalman Filter:

It can be viewed as a practice of reordering technique whose established realizations comprise batch processing, smoothing, and forward/backward processing. Thus, it would be interesting to compare the proposed algorithm to another measurement reordering solution to see if the problem is unique to the PF. The RHKF would be a good example here since it is a recursive estimator where at each time step an optimization problem is solved by using a time window of measurements to obtain the state estimates. The Kalman filtering framework is extended to include a receding horizon with an augmented state vector and an augmented error covariance matrix. It is known that the RHKF provides more robust and accurate results than the standard extended Kalman filter.it is batter to perform batch processing.

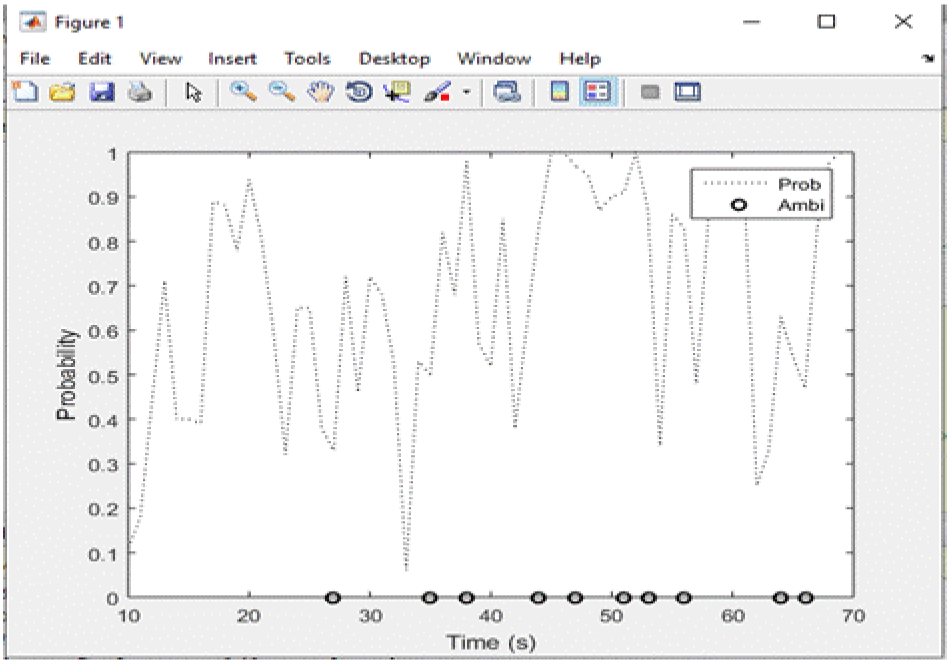

Figure 1:Time history of RMSE

Figure 1 represents the case with relatively small process noise. and object detection space are measured

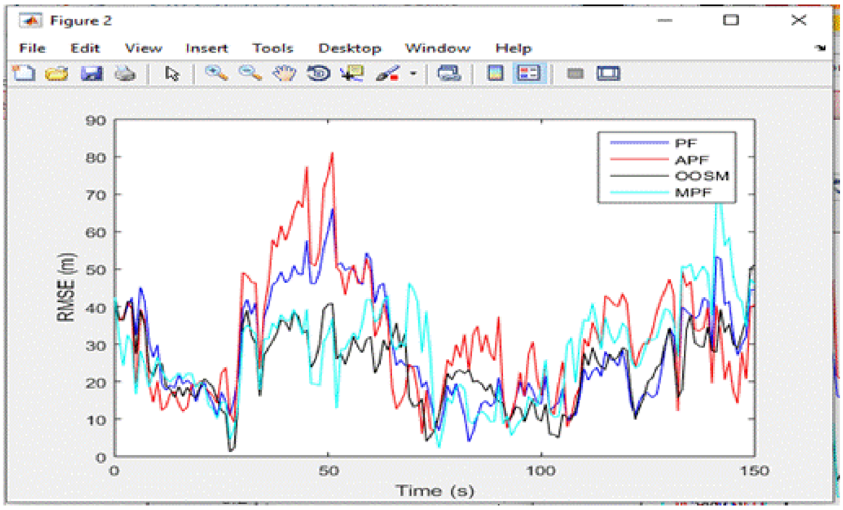

Figure:2Time history of RMSE

In the fig 2 we get the RMSE of the each pf, Apf, OOSM ,mpf all the resampling values are calculated between 50- 150.

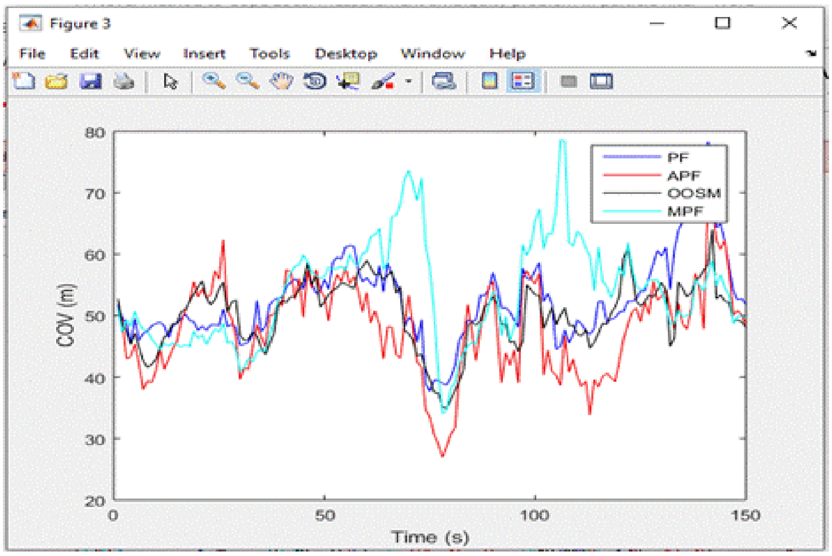

Figure : 3Time history of covariance

In fig 3 On the other hand, the PF-based algorithms showed relatively robust behaviour. The APF still hurt from the big process error and biases as in Case 2. The OOSMPF did not show exceptional performance in terms of RMSE for all cases. Instead, the OOSMPF provided more confident estimates than the PF and the MPF.

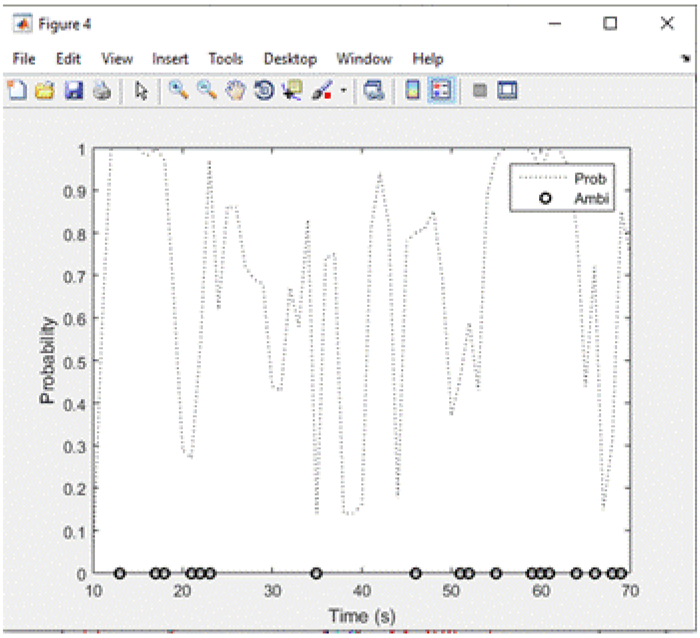

Figure :4Time history of RMSE

In Fig 4 the MPF shows alike behaviour as the PF for all the cases in relations of the RMSE and the covariance. This is because the ambiguous measurement update occurs occasionally due to local ambiguity and, therefore, the modes are not definitely separated.

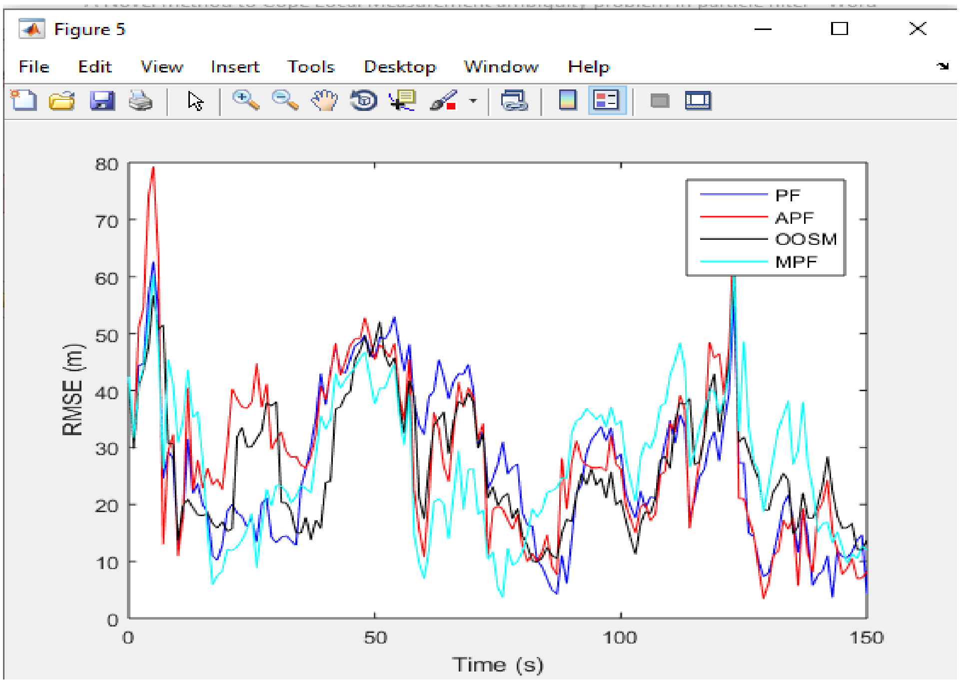

Figure:5Time history of RMSE

Fig. 5 shows the time history of the RMSE, (12), of each filtering algorithm based on its execution time and small process noise.

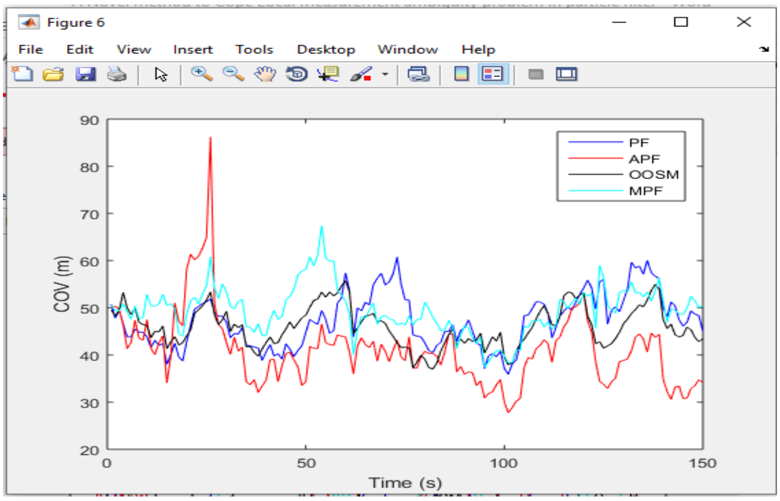

Figure 6: estimated covariance of RMSE

In this fig(6) is shows the estimate calculated covariance. We observed that the PF and the MPF show similar RMSE behaviour as the OOSMPF. Therefore, we present RMSE plots to show different results of the RHKF, the APF, and the OOSMPF, omitting those of the PF and the APF. The average RMSEs during 50–150 s after the converging track for all the algorithms On the other hand, the OOSMPF successfully dealt with the ambiguous measurements and proare presented in Table II. It was observed that, with small process noises, the RMSE of the PF-based algorithms did not reveal any momentous difference among each other. The APF provided smaller covariance's than other PF-based algorithms as also discussed in the literature [16]. However, the RHKF has much smaller covariance, which is not consistent with its estimation performance. This is because the linearized measurement model in the Kalman filter-based algorithm failed to approximate the surrounding terrain, which contains many inflection points. Thus, the RHKF provided tainted state estimates, whereas the filter was very certain with the filtering results. Unlike the RHKF, the PF-based algorithms have larger covariance since they faced less certain measurement updates by considering terrain profile covered by the prior density.

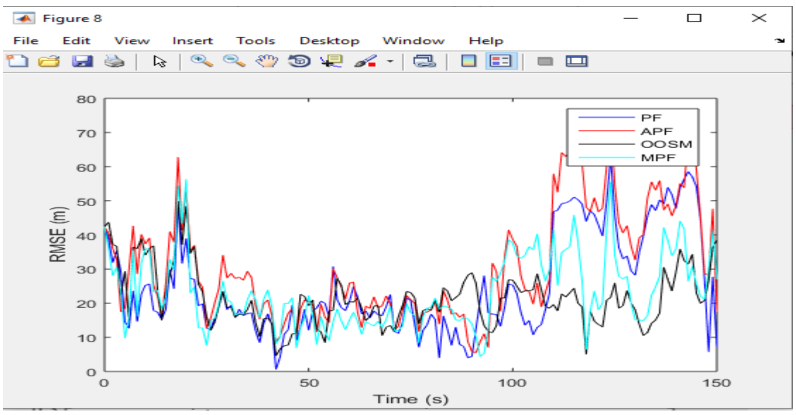

Figure 8 : performance of RMSE

Fig 8. The sampling shows the best performance among the filtering algorithms. The average RMSE of the RHKF, but the filter shows comparatively unstable behaviour, which is seen to be due to model nonlinearity. The APF is degraded while its estimated covariance is still slighter. If the process noise is large, a single point cannot describe well. In such cases, the use of the APF results in poor performance. On another one method of OOSM particle method is completely dealt with unknown measurements and provided more confident and accurate state estimates

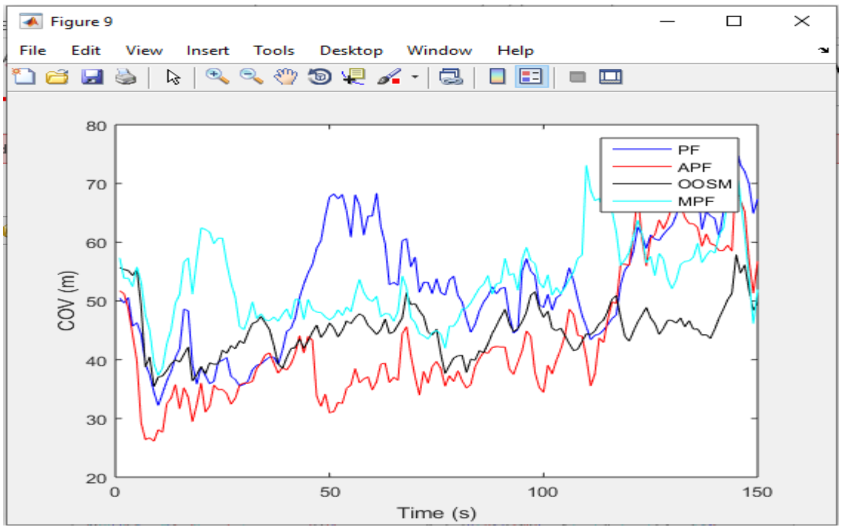

Figure 9: Ambiguous measurements of Time

In Fig. 9, the time examples of occurrences of the ambiguous measurements, which produced larger posterior covariance than the prior covariance by definition, in a period of a MPF run are marked as circles. The dotted line denotes probability of having at furthermost one mode with the critical bandwidth evaluated by the mode estimation method. In this method low value of probability value depend on existing multimodal distribution Fig. 9 demonstrates that the covariance upsurge does not essentially induce multimodal posterior distribution. Multimodal deliveries were often originate during the run but not upheld for a long stretch. If this is the case where the dimension ambiguity occurs for a long stretch, the MPF would be a better practice

CONCLUSION

In the measurement we will evaluate the target size by the help of particle. Each and every measurements is not give the actual location of the object but it will give some approximate location .so this failure avoid by the help of sampling method get the actual position of the individual object Compared to the RHKF and other methods based on the SIR PF, the proposed method provided better performance in terms of RMSE and estimated covariance. Theoretical investigation on the measurement ambiguity and object detection at various environment as a future work.

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