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Multiple Target Tracking Using Particle Filter Based Multi-scan Joint Probabilistic Data Association Filter

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Abstract: In this paper, a particle filter based multi-scan JPDA filter is proposed to deal with the data association problem in multiple target tracking. In the proposed multi-scan JPDA algorithm, the distributions of interest are the marginal filtering distributions for each of the targets, and these distributions are approximated with particles. The multi-scan JPDA algorithm examines the joint association events in a multi-scan sliding window and calculates the marginal posterior probability based on the multi-scan joint association events. The proposed algorithm is illustrated via an example involving tracking of two slowly maneuvering targets based on resolved measurements.

Key Words: Multiple Target Tracking, Particle Filter, Multi-scan JPDA.

1 Introduction

In the process of multiple target tracking, two distinct problems have to be solved jointly: data association and state estimation. Data association is a key problem in multiple targets tracking and determines which measurement corresponds to which target. A large number of strategies are available to solve the data association problem.

The multiple hypothesis tracking (MHT) [1] was proposed by Read in 1979. The MHT attempts to keep track of all the possible association hypotheses over time. This is an NP-hard problem, since the number of association hypotheses grows exponentially over time. Thus methods are required to reduce the computational complexity.

Compared with MHT, the nearest neighbor (NN) algorithm [2] is computationally simple and easily to implement. In NN algorithm, each target is associated with the closest measurement in the target space. However, such a simple procedure prunes away many feasible hypotheses.

In this respect the joint probabilistic data association (JPDA) filter [2, 3] is more appealing. At each time step infeasible hypotheses are pruned away using a gating procedure. A filtering estimate is then computed for each of the remaining hypotheses, and combined in proportion to the corresponding posterior hypothesis probabilities. The main shortcoming of the JPDA filter is that, to maintain tractability, the final estimate collapses to a single Gaussian, thus discarding pertinent information. Subsequent work addressed this shortcoming by proposing strategies to reduce the number of mixture components in the original mixture to a tractable level [4, 5]. Still, many feasible hypotheses may be discarded by the pruning mechanisms.

The probabilistic multiple hypotheses tracker (PMHT) [6, 7] assumes the association variables to be independent from the pruning work, which leads to an incomplete data problem that can be efficiently solved using the expectation maximization (EM) algorithm [8]. However, the PMHT is a batch strategy, and thus not suitable for online applications. The standard version of the PMHT is also generally outperformed by the JPDA filter. Some of the reasons for this, and a number of possible solutions, are discussed in [9].

Even though methods to solve the data association problem do not usually rely on linear and Gaussian models, this assumption is often made to simplify hypothesis evaluation for target originated measurements. For example, nonlinear models can be accommodated by suitable linearization using EKF. As for EKF, however, the performance of the algorithms degrades as the nonlinearities become more severe.

In recent years, particle filter has been introduced to estimate non-linear non-Gaussian dynamic processes for multiple target tracking. A stochastic simulation Bayesian method is reported in [10] for multiple target tracking. In this method, random samples are used to represent the posterior distribution of the target state. However, only one target is considered in the example outlined. More recently, particle filter has been applied with great success to different fields of multiple target tracking including computer vision [11, 12], mobile robot localization [13, 14] and air traffic control [15, 16]. The various methods adopted fall into the following five categories.

The first category introduces MCMC strategies to calculate the association probabilities. In [15] the distribution of the association hypotheses is calculated using a Gibbs sampler [17] at each time step. The method is similar in spirit to the one described in [18] which uses the MCMC techniques [19] to compute the correspondences between image points within the context of stereo reconstruction. The main problem with these MCMC strategies is that they are iterative in nature and take an unknown number of iterations to converge. They are thus not entirely suitable for online applications.

The second category treats the association variables as state variables. In [20], the association variables are sampled from an optimally designed importance distribution. The method is intuitively appealing since the association hypotheses are treated in a similar fashion to the target state, so that the resulting algorithm is non-iterative. It is, however, restricted to jump Markov linear systems (JMLS) [21]. An

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extension of this strategy based on the auxiliary particle filter (APF) [22] and the UKF, which is applicable to general jump Markov systems (JMS), is presented in [23]. Another similar approach is described in [24]. Samples for the association hypotheses are generated from an efficient proposal distribution based on the notion of a soft-gating of the measurements.

The third category combines the JPDAF with particle techniques to accommodate general nonlinear and non-Gaussian models [13, 25, 26, 27]. The data association problem is addressed directly in the context of particle filtering.

The fourth category relates to multiple target tracking problems based on raw measurements [28, 29]. These, so-called, track before detect (TBD) strategies construct a generative model for the raw measurements in terms of a multi-target state hypothesis, thus avoiding an explicit data association step. However, such measurements are not always readily available in practical systems, and may lead to a larger computational complexity.

The above four categories of methods use particles whose dimension is the sum of those of the individual state spaces corresponding to each target. They all suffer from the curse of dimensionality problem since with the increase in the number of targets, the size of the joint state-space increases exponentially. If care is not taken in the design of proposal distributions an exponentially increasing number of particles may be required to cover the support of the multi-target distribution and maintain a given level of accuracy.

The fifth category avoids the dimension problem through exploring the particle filter' ability to track multiple targets in a single-target state space. As pointed out in [30], particle filters may perform poorly when the posterior distribution of the target state is multiple-mode due to ambiguities and multiple targets in single-target state space. To circumvent this problem, a mixture particle filter method is introduced in [30], where each mode is modeled with an individual particle filter that forms part of the mixture. The filters in the mixture interact only through the computation of the importance weights. By distributing the resampling step to individual filters, the well known problem of sample impoverishment is avoided, which is largely responsible for losing track.

In this work, a novel method named particle filter based multi-scan JPDA is proposed for multiple target tracking. In the proposed approach, the distributions of interest are the marginal filtering distributions for each of the targets, which is approximated with particles [31]. The multi-scan JPDA filter algorithm examines the joint association hypothesis in a multi-scan sliding window and calculates the posterior marginal probability based on the multi-scan joint association hypothesis. Compared with the single scan JPDA method, the multi-scan JPDA method uses richer information, which results in better estimated probabilities.

The rest of the paper is organized as follows. In Section 2 the basic theory and procedure of particle filter for state estimation are provided. The data association method based on multi-scan JPDA is discussed in Section 3. The simulation results are shown in Section 4 and the paper is summarized in Section 5.

2 Basic Theory of Particle Filter

To define the problem of tracking, consider a dynamic system represented by the state equation:

$$x_k = f(x_{k-1}, v^*_{k-1}), \tag{1}$$

where x is the state, f is a possibly nonlinear function, and v^* is the known process noise with a zero mean Gaussian distribution. The objective of tracking is to recursively estimate x_k from a sequence of measurements up to time step k, $z_{1:k} = \{z_1, z_2, \cdots, z_k\}$. The observation model is described as follows,

$$z_k = h(x_k, n_k), \tag{2}$$

where h is a possibly nonlinear function. n is the observation noise with a zero mean Gaussian distribution. From the Bayesian perspective, the tracking problem is to recursively calculate the posterior distribution $p(x_k|z_{1:k})$.

In this paper, a particle filter is considered to solve the state estimation problem due to its ability to tackle the nonlinear and non-Gaussian systems. The posterior distribution $p(x_k|z_{1:k})$ is approximated by a set of particles with associated weights. The detailed introduction about particle filter algorithm can be found in [32]. The procedures associated with the standard particle filter are listed in the following:

Algorithm 1: Particle Filter Algorithm

(1) **Initialization**: Sample initial particles $\{x^i_0, i = 1, ..., H\}$ from the initial posterior distribution $p(x_0)$ and set the weights w^i_0 to $\frac{1}{H}$, $i = 1, ..., H$. H is the number of particles.

(2) **Prediction**: Particles at time step $k-1$, $\{x^i_{k-1}, i = 1, ..., H\}$, are passed through the system model (3) to obtain the predicted particles at time step k, $\{\hat{x}^i_k, i = 1, ..., H\}$:

$$\hat{x}^i_k = f(x^i_{k-1}, v^{*,i}_{k-1}), \tag{3}$$

where $v^{*,i}_{k-1}$ is a sample drawn from the known zero mean Gaussian distribution.

(3) **Update**: Once the observation data, z_k, is measured, evaluate the importance weight of each predicted particle and obtain the normalized weight for each particle (4).

$$\hat{w}^i_k = p(z_k|\hat{x}^i_k), \quad w^i_k = \frac{\hat{w}^i_k}{\sum_{i=1}^{H} \hat{w}^i_k} \tag{4}$$

Thus at time step k we can obtain the estimate of the state, $\tilde{\hat{x}}_k = \sum_{i=1}^{H} w^i_k \hat{x}^i_k$.

(4) **Resample** : Resample the discrete distribution $\{w^i_k : i = 1, \cdots, H\}$ H times to generate particles $\{x^j_k : j = 1, \cdots, H\}$, so that for any j, $Pr\{x^j_k = \hat{x}^i_k\} = w^i_k$. Set the weights w^i_k to $\frac{1}{H}$, $i = 1, ..., H$, and move to Stage 2.

3 Multiple Target Tracking Using Particle Filter Based Multi-scan JPDA Filter

The number of targets (M) to be tracked is assumed as fixed and known, where each target track has been initiated, and our objective is to maintain the tracks. Each target is parameterized by a state $x_{m,k}$, where m denotes the mth target and k denotes time step k. The combined state, $x_k = (x_{1,k}, \cdots, x_{M,k})$, is the concatenation of the individual target states. The individual targets are assumed to evolve independently according to the Markovian dynamic models $p_m(x_{m,k}|x_{m,k-1})$. The observation vector z_k is composed of multiple sensor measurements $\{z_{j,k}, j = 1, \cdots, N_k\}$, where N_k is the total number of measurements. It is assumed that there are no unresolved measurements (i.e., measurements associated with two or more targets simultaneously), any measurement is either associated with a single target or caused by clutter. Clutter is modeled as independently and identically distributed (IID) with uniform spatial distribution over the surveillance area.

In the particle filter based JPDA algorithm, the distributions of interest are the marginal filtering distributions for each of the targets $p_m(x_{m,k}|z_{1:k}), m = 1 \cdots M$, and these distributions are approximated with particles, $\{\hat{x}^i_{m,k}, i = 1 \cdots H, m = 1 \cdots M\}$, and their associated weights $\{w^i_{m,k}, i = 1 \cdots H, m = 1 \cdots M\}$, as in (5),

$$p_m(x_{m,k}|z_{1:k}) = \sum_{i=1}^{H} w^i_{m,k} \delta(x_{m,k} - \hat{x}^i_{m,k}). \quad (5)$$

At each time step, when the new observation vector arrives, the marginal filtering distributions for each of the targets are updated through the Bayesian sequential estimation recursions [31].

In the standard single scan JPDA framework, a track is updated with a weighted sum of the measurements which could have reasonably originated from the target in track. The only information the standard JPDA algorithm uses is the measurements on the present scan and the state vectors. If more scans of measurements are used, additional information is available resulting in better computed probabilities [2]. Since the tracking systems are unable to store all of the measurements from all the scans, a Bayesian tracking system can at best rely on a sliding window of scans. In [33], the single scan JPDA filter is extended to the multiple scan JPDA filter for tracking multiple targets. And in this work the multiple scan JPDA filter is developed in a particle filter framework.

The multiple scan JPDA calculation examines multiple scan joint association events [33]. The measurement to target association event of multiple scan is defined as $\lambda_{k-L+1:k}$, where L denotes the length of the multiple scan sliding window. The multiple scan joint association events are mutually exclusive, and they form a complete set $\Lambda_{k-L+1:k}$ [34]. $\lambda_{k-L+1:k}$ is composed by the association vectors at each scan in the sliding window, $\lambda_{k-L+1:k} = (\theta_{k-L+1}, \theta_{k-L+2}, \cdots, \theta_k)$. The elements of the association vector at time step k, $\theta_k = (\zeta_{1,k}, \cdots, \zeta_{j,k}, \cdots, \zeta_{N_k,k})$ are given by,

$$\zeta_{j,k} = \begin{cases} 0, & if\ z_{j,k}\ is\ due\ to\ clutter, \\ m \in \{1 \cdots M\}, & if\ z_{j,k}\ is\ from\ target\ m. \end{cases} \quad (6)$$

The heart of the new algorithm is to find the posterior probability for the joint association event of multiple scans. That is to calculate $p(\lambda_{k-L+1:k}|z_{1:k})$ and it can be written as,

$$\begin{aligned} & p(\lambda_{k-L+1:k}|z_{1:k}) \\ \propto\ & p(z_k \cdots z_{k-L+1}|\lambda_{k-L+1:k}, z_{1:k-L}) p(\lambda_{k-L+1:k}|z_{1:k-L}) \\ \propto\ & p(z_k \cdots z_{k-L+1}|\lambda_{k-L+1:k}, z_{1:k-L}) p(\lambda_{k-L+1:k}), \end{aligned} \quad (7)$$

where the conditioning of $\lambda_{k-L+1:k}$ on the history of measurements before the sliding window has been eliminated.

The distribution of the measurements in the sliding window based on a specific association event is given by,

$$\begin{aligned} & p(z_k \cdots z_{k-L+1}|\lambda_{k-L+1:k}, z_{1:k-L}) \\ & = \textstyle\prod_{s=1}^{L}[\prod_{j=1}^{N_{k-L+s}} p(z_{j,k-L+s}|\lambda_{k-L+1:k}, z_{1:k-L})]. \end{aligned} \quad (8)$$

To reduce the notation, the index of the scan s in the sliding window is denoted by $k_s = k - L + s$. Then we can obtain,

$$\begin{aligned} & p(z_k \cdots z_{k-L+1}|\lambda_{k-L+1:k}, z_{1:k-L}) \\ = & \textstyle\prod_{s=1}^{L}[\prod_{j=1}^{N_{k_s}} p(z_{j,k_s}|\lambda_{k-L+1:k}, z_{1:k-L})] \\ = & \textstyle\prod_{s=1}^{L}[\prod_{j\in I_{0,k_s}} p_c(z_{j,k_s}) \cdot \prod_{j\in I_{k_s}} p(z_{j,k_s}|x_{\zeta_{j,k_s},k_s})] \\ = & \textstyle\prod_{s=1}^{L}[(V)^{-C_{k_s}} \cdot \prod_{j\in I_{k_s}} p(z_{j,k_s}|x_{\zeta_{j,k_s},k_s})], \end{aligned} \quad (9)$$

where $I_{0,k_s} = \{j \in \{1, \cdots, N_{k_s}\} : \zeta_{j,k_s} = 0\}$ and $I_{k_s} = \{j \in \{1, \cdots, N_{k_s}\} : \zeta_{j,k_s} \neq 0\}$ are respectively the subsets of measurement indices corresponding to clutter measurements and measurements from the targets being tracked, on scan k_s. p_c denotes the clutter likelihood model, which is assumed to be uniform over the volume of the surveillance area V. The volume of the surveillance area could be calculated as per $V = 2\pi R_{max}$, where R_{max} is the maximum range of the sensor. C_{k_s} is defined as the number of clutter measurements.

The joint association prior $p(\lambda_{k-L+1:k})$, can be calculated as in (10) according to [2], [35],

$$\begin{aligned} & p(\lambda_{k-L+1:k}) \\ = & \textstyle\prod_{s=1}^{L}[\frac{C_{k_s}!\varepsilon}{N_{k_s}!} \prod_{m=1}^{M} (P_D)^{\delta_m(\theta_{k_s})} (1 - P_D)^{1-\delta_m(\theta_{k_s})}], \end{aligned} \quad (10)$$

where ε is a "diffuse" prior [35] and P_D is the detection probability. $\delta_m(\theta_{k_s})$ is a binary variable and set to one if the mth target is assigned with a measurement in the event θ_{k_s}.

The posterior probability for the joint association event of multiple scans is obtained as,

$$\begin{aligned} & p(\lambda_{k-L+1:k}|z_{1:k}) \\ & \propto p(\lambda_{k-L+1:k}) \textstyle\prod_{s=1}^{L}[(V)^{-C_{k_s}} \cdot \prod_{j\in I_{k_s}} p(z_{j,k_s}|x_{\zeta_{j,k_s},k_s})]. \end{aligned} \quad (11)$$

The posterior probability that the jth measurement is associated with the mth target on scan k, β_{jm}, is calculated by summing over the probabilities of the corresponding joint association events via (12),

$$\begin{aligned} \beta_{jm} &= p(\zeta_{j,k} = m|z_{1:k}) \\ &= \textstyle\sum_{\{\lambda_{k-L+1:k}\in\Lambda_{k-L+1:k}\ :\ \zeta_{j,k}=m\}} p(\lambda_{k-L+1:k}|z_{1:k}). \end{aligned} \quad (12)$$

These approximations can, in turn, be used in (13) to approximate the target likelihood according to [31],

$$p_m(z_k|x_{m,k}) = \beta_{0m} + \sum_{j=1}^{N_k} \beta_{jm} p(z_{j,k}|x_{m,k}), \quad (13)$$

where β_{0m} is the posterior probability that the mth target is undetected. Finally, setting the new importance weights to,

$$\begin{aligned} & w^i_{m,k} \propto w^i_{m,k-1} \frac{p_m(z_k|\hat{x}^i_{m,k}) p_m(\hat{x}^i_{m,k}|x^i_{m,k-1})}{q_m(\hat{x}^i_{m,k}|x^i_{m,k-1})}, \\ & \textstyle\sum_{i=1}^{H} w^i_{m,k} = 1, \end{aligned} \quad (14)$$

where $q_m(\hat{x}^i_{m,k}|x^i_{m,k-1})$ is the proposal distribution, which is used to generate the predicted particles. The equation (14) leads to the sample set $\{w^i_{m,k}, \hat{x}^i_{m,k}\}^H_{i=1}$ being approximately distributed according to the marginal filtering distribution $p_m(x_{m,k}|z_{1:k})$.

A summary of the particle filter based multiple scan JPDA filter algorithm is presented in what follows. Assuming that the sample sets $\{w^i_{m,k-1}, x^i_{m,k-1}\}^H_{i=1}, m = 1\cdots M$, are approximately distributed according to the corresponding marginal filtering distributions at the previous time step $p_m(x_{m,k-1}|z_{1:k-1}), m = 1\cdots M$, the algorithm proceeds as follows at the current time step.

Algorithm 3: Particle Filter Based Multi-scan JPDA Filter

1) For $m = 1\cdots M, i = 1\cdots H$, generate predicted particles for the target states $\hat{x}^i_{m,k} \sim q_m(\hat{x}^i_{m,k}|x^i_{m,k-1})$.
2) For $m = 1\cdots M$, calculate $\tilde{x}_{m,k}$, the pre-approximation of $x_{m,k}$, which is to be substituted into (11) to calculate the posterior probability of the joint association event in multiple scan, $p(\lambda_{k-L+1:k}|z_{1:k})$.

$$\tilde{x}_{m,k} = \sum_{i=1}^{H} w^i_{m,k-1}\hat{x}^i_{m,k}. \tag{15}$$

3) Enumerate all the valid joint measurement to target association events in the sliding window $k-L+1:k$ to form the set $\Lambda_{k-L+1:k}$.
4) For each $\lambda_{k-L+1:k} \in \Lambda_{k-L+1:k}$, compute the posterior probability of the joint association event in multiple scan, $p(\lambda_{k-L+1:k}|z_{1:k})$, via (11).
5) For $m = 1\cdots M, j = 1\cdots N_k$, compute the marginal association posterior probability, β_{jm}, via (12).
6) For $m = 1\cdots M, i = 1\cdots H$, compute the target likelihood, $p_m(z_k|\hat{x}^i_{m,k})$, via (13).
7) For $m = 1\cdots M, i = 1\cdots H$, compute and normalize the particle weights via (14).
8) Resample the discrete distribution $\{w^i_{m,k} : i = 1,\cdots,H\}$ H times to generate particles $\{x^j_{m,k} : j = 1,\cdots,H\}$, so that for any j, $Pr\{x^j_{m,k} = \hat{x}^i_{m,k}\} = w^i_{m,k}$. Set the weights $w^i_{m,k}$ to $\frac{1}{H}$, $i = 1,...,H$, and move to Stage 1.

4 Simulation Results and Analysis

The simulation is carried out for tracking two slow-maneuvering targets in clutter. The Wiener process acceleration model (16) is chosen as the motion model for the two targets.

$$X_k = \Phi X_{k-1} + \Gamma v_{k-1} \tag{16}$$

The process noise $v_{k-1} = [v_{p_x}, v_{\gamma_x}, v_{a_x}, v_{p_y}, v_{\gamma_y}, v_{a_y}]^T_{k-1}$, is a zero mean Gaussian white noise process with standard deviations of $1\ m\ (\sigma_{v_{p_x}})$, $1\ m/s\ (\sigma_{v_{\gamma_x}})$, $20\ m/s^2\ (\sigma_{v_{a_x}})$, $1\ m\ (\sigma_{v_{p_y}})$, $1\ m/s\ (\sigma_{v_{\gamma_y}})$ and $20\ m/s^2\ (\sigma_{v_{a_y}})$.

At time step 1, target one starts at location $[-310,\ 310]$ in $x-y$ Cartesian coordinates in meters with the initial velocity (in m/s) $[10,\ -400]$. Target two starts at location (in m) $[-310,\ -19000]$ with the initial velocity (in m/s) $[10,\ 400]$. The length of each simulation run is 50 seconds.

A track-while-scan (TWS) radar is positioned at the origin of the plane. The measurement equation is as follows:

$$Z_k = h(X_k) + n_k, \tag{17}$$

where $Z_k = [z_1, z_2]_k$ is the observation vector. z_1 is the distance between the radar and the target, and z_2 is the bearing angle. The measurement noise $n_k = [n_{z_1}, n_{z_2}]_k$ is a zero mean Gaussian white noise process with standard deviations of 20 $m\ (\sigma_{z_1})$ and $0.01\ rad\ (\sigma_{z_2})$. Resolution of the sensor is selected after from [36] (twice of the standard deviations of the measurement noise).

The sampling interval is $\Delta T = 1s$ and it is assumed that the probability of detection $P_D = 0.9$ for the radar. For generating measurements in simulations, the clutter is assumed uniformly distributed with density $1 \times 10^{-6}/m^2$.

In the particle filter based multi-scan JPDA methods, each target model is assigned with 500 particles. The algorithm is initialized with Gaussians around the initial states of the true targets, and the standard deviations of the two Gaussian distributions are chosen equally as $\{10\ m, 10\ m/s, 5\ m/s^2, 10\ m, 10\ m/s, 5\ m/s^2\}$.

In the simulations carried out, the length of the multiple scan sliding window (L) varies from 1 to 3. The corresponding particle filter based multi-scan JPDA methods with $L = 1, 2, 3$ are utilized to track two slow-maneuvering targets individually. A comparison to the standard JPDA filter is also studied on the same simulation setup. The simulation results are obtained from 1000 Monte Carlo runs. Fig. 1 shows the true trajectories of the two targets and Fig. 2 shows the distance between the two targets along time, through which we can see that the two targets reach the smallest distance at time step 25. The RMSEs in position for the two targets are respectively shown in Fig. 3 and Fig. 4, where PFJPDA represents the particle filter based JPDA filter with its following number in the bracket (e.g. (1)) denoting the scan number (L). The performance of the four methods is also compared in Table. 1. The swap rate (SR) is defined as the ratio of the number of simulations, in which the two targets swap, to the total number of simulations.

Compared with the standard JPDA method (based on extended Kalman filter), the particle filter based JPDA methods (single scan and multiple scan) are much more accurate and robust, at the cost of longer computing time. This verifies that when dealing with nonlinear problem (nonlinear observation equation) and large random acceleration (large process noise), the performance of particle filter is better than extended Kalman filter using local linearization.

In the comparison between the three particle filter based JPDA methods (L=1, 2, 3 respectively), from Fig. 3 and Fig. 4 it can be seen that there is no significant deference between the three methods except around time step 25, when the two targets are very close to each other (Fig. 2). As the scan number increases, the RMSE (in position) of the corresponding algorithm decreases significantly around time step 25 (Fig. 3 and Fig. 4). This verified that the particle filter based multi-scan JPDA method provides better performance especially when the targets are very close. The additional information of more scans improve the association probabilities in such critical situation, resulting in lower estimation errors (RMSE) and larger robustness (tracking loss rate).

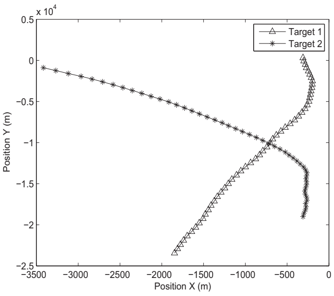

Fig. 1: True trajectories of the two slow-maneuvering targets

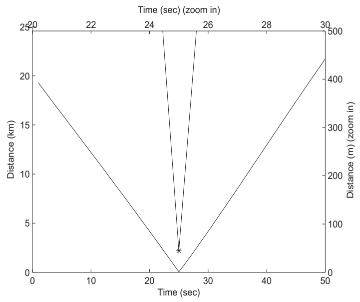

Fig. 2: Distance between the two targets (- distance; -* zoom in distance)

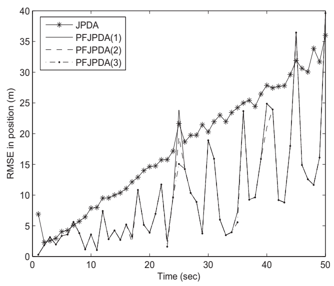

Fig. 3: Target 1: RMSE in position using standard JPDA filter, particle filter based multi-scan JPDA algorithms with scan number equals to 1, 2 and 3 respectively

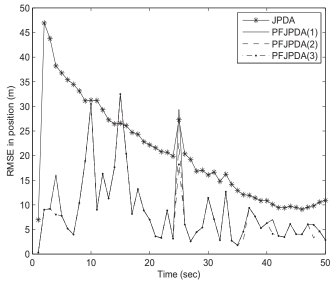

Fig. 4: Target 2: RMSE in position using standard JPDA filter, particle filter based multi-scan JPDA algorithms with scan number equals to 1, 2 and 3 respectively

Table 1: Performance Comparison

	RMSE (m)	ET (s)	TLR	SR
JPDA	T1: 20.24, T2: 22.87	0.07	24%	0
PFJPDA(1)	T1: 13.21, T2: 11.36	1.28	0	0
PFJPDA(2)	T1: 12.92, T2: 11.01	1.54	0	0
PFJPDA(3)	T1: 12.75, T2: 10.67	1.8	0	0

5 Conclusions

A new algorithm is proposed for multiple target tracking in the particle filter framework. In order to tackle the data association problem in multiple target tracking, the particle filter based multi-scan JPDA filter is adopted. The marginal filtering distributions for each of the targets is approximated with particles. The proposed algorithm examines the joint association hypothesis in a multi-scan sliding window and calculates the marginal posterior probability based on the multi-scan joint association hypothesis. Compared with the single scan JPDA method, the multi-scan JPDA method uses richer information, which results in better estimated probabilities.

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