Progress In Electromagnetics Research B, Vol. 50, 365–381, 2013

A MULTI-SCAN MIXTURE PARTICLE FILTER FOR JOINT DETECTION AND TRACKING OF MULTIPLE TARGETS

Jing Liu*, **Chongzhao Han, Xianghua Yao, and Feng Lian**

School of Electronics and Information Engineering, Xi'an Jiaotong University, Xi'an, P. R. China

Abstract—In this paper, a novel algorithm named multi-scan mixture particle filter is proposed for joint detection and tracking for a varying number of targets. The posterior distribution of multiple target state in a single-target state space is a multi-mode distribution with each mode corresponding to either a target or clutter. A general global posterior distribution is adopted in this work, which consists of existing components and new components. The new components are generated at each time step to capture the new modes due to newly appeared targets or clutter. In order to distinguish targets from clutter, multiple scan information is incorporated. The history of each component's associate weights is stored in a multi-scan sliding window, which is used to judge whether the component is from a target or clutter. Moreover, a novel sampling method which combines the likelihood sampling and prior sampling is proposed to draw particles from the desired parts of the state space at each time step. From the simulation results, it could be seen that the proposed algorithm can effectively detect the appearance/disappearance of the targets as well as track the existing target.

1. INTRODUCTION

Multiple target tracking (MTT) is applied widely in the areas of autonomous surveillance, computer vision, audio signal processing and wireless communication [1–6]. Recently, joint detection and tracking for multiple targets has been drawn much attention. A lot of approaches have been proposed to solve the joint detection and tracking problem. The approaches can be categorized into single-scan and multi-scan algorithms by the way in which they process

Received 20 February 2013, Accepted 15 April 2013, Scheduled 17 April 2013

* Corresponding author: Jing Liu (elelj20080730@gmail.com).

measurements [7]. Single scan algorithms estimate the current states of targets based on their previously estimated states and the current scan of measurements, while multi-scan algorithms estimate the current states of targets based on their previously estimated states, multiple past scans and the current scan of measurements.

Multiple hypothesis tracking (MHT) [8] is a multi-scan tracking algorithm, which maintains multiple hypotheses associating past measurements with targets.

In contrast, the well-known JPDA algorithm [9] belongs to the single-scan algorithms. At each time step, JPDA enumerates all possible associations and computes association probabilities.

In recent years, the approaches based on joint multitarget probability density (JMPD) [10], which captures uncertainty about the number of targets as well as their individual states, are used widely in the joint detection and tracking.

Since the JMPD is a high-dimensional entity that can not be computed in closed form, particle filters (PFs) have been used to approximate the JMPD in realistic scenarios involving tracking multiple targets [11]. While the particle filter based JMPD approach is theoretically sound, it demands intense computation, with a huge number of particles required to explore different dimensional state-spaces for target detection.

In the above methods, the dimension of the state vector is proportional to the number of targets in the surveillance region. They suffer from the curse of dimensionality problem since as the number of targets increases, the size of the joint state-space increases exponentially. Alternative ways of detecting multiple targets in clutter-governed environments have been presented in the literature. As an example, Bayesian [12, 13] and artificial neural networks [14, 15] techniques have been successfully used, considering a single-scan strategy approach. As pointed out in [16], the posterior distribution of multiple target state is a multi-mode distribution and each mode corresponds to either a target or clutter. A mixture particle filter method is developed in [16], where each mode is modeled with an individual particle filter that forms part of the mixture. The mixture particle filter avoids the dimension problem by exploring the particle filter's ability to track multiple targets in a single-target state space. However, the proposed algorithm can not handle the new target appearance problem since it can not generate any new particle filters during the tracking process to represent the new modes occurred due to newly appeared targets. Moreover, the algorithm is utilized in a clutter-free environment. This algorithm could also be used considering clutter reduction techniques as a pre-processing stage, as the ones used in ground [17] and/or sea [18] clutter-governed environments.

In this paper, a new algorithm named multi-scan mixture particle filter is proposed for joint detection and tracking for a varying number of targets.

Different from [16], a general global posterior distribution is adopted in this work, which consists of existing components and new components. The existing components could be further divided into target components and undetermined components (including potential targets and clutter). With the undetermined components, it is clear to represent the uncertain modes, which could be target or clutter in future time steps but can not be determined at the current time step. The new components are generated at each time step to capture the new modes due to newly appeared targets or clutter. In order to distinguish targets from clutter, multiple scan information is incorporated. For each component, its associate weights are stored in a multi-scan sliding window. The history of each component's associate weights within the sliding window could be used to judge whether the component is from a target or clutter. Moreover, a novel sampling method which combines the likelihood sampling and prior sampling is proposed to draw particles from the desired parts of the state space at each time step. From the simulation results, it could be seen that the proposed algorithm can effectively detect the appearance/disappearance of the targets as well as track the existing target.

The rest of the sections are organized as follows, firstly, the general global posterior distribution approximated with mixture particle filters is introduced in Section 2. The efficient method to distinguish target from clutter based on multi-scan information is introduced in Section 3. In Section 4, the novel sampling method which combines the likelihood sampling and prior sampling is proposed to draw particles from the desired parts of the state space. The joint detection and tracking process is introduced in Section 5, and the simulation results and analysis are listed in Section 6. The paper is summarized in Section 7.

2. THE GLOBAL POSTERIOR DISTRIBUTION APPROXIMATED WITH MIXTURE PARTICLE FILTERS

The global posterior distribution is modeled as an M-component non-parametric mixture model, with each component corresponding to either a target or clutter in [16]. Though the proposed mixture particle filter algorithm can perform the computation operations for the components including merging, splitting, re-clustering, it can not generate new components during the tracking process to capture the new modes due to new targets appeared anywhere in the surveillance region. In this section, a general global posterior distribution $p(x_k|z_{1:k})$, which consists of the existing components propagated from previous time step and the new components generated at the current time step, is provided as follows:

$$p(x_k|z_{1:k}) = \sum_{m=1}^{M} \pi_{m,k}^{E} p_m^E(x_k|z_{1:k}) + \sum_{n=1}^{N} \pi_{n,k}^{N} p_n^N(x_k|z_{1:k}), \tag{1}$$

where $p_m^E(x_k|z_{1:k})$ and $\pi_{m,k}^{E}$ denote the filtering distribution for the mth existing component and its associate weight, and $p_n^N(x_k|z_{1:k})$ and $\pi_{n,k}^{N}$ for the nth new component, M and N denote the total number of existing components and new components respectively.

The posterior distribution of each component is approximated with an individual particle filter with NP particles, e.g., for the mth existing component,

$$p_m^E(x_k|z_{1:k}) = \sum_{i=1}^{NP} w_{m,k}^{E,i} \delta\left(x_k - x_{m,k}^{E,i}\right), \tag{2}$$

where $x_{m,k}^{E,i}$ is the ith particle from the particle filter corresponding to the mth existing component, and $w_{m,k}^{E,i}$ is its associate weight.

The existing components can be further divided into target components and non-determined components, which evolve according to the following general dynamic model,

$$x_k = f(x_{k-1}) + v_{k-1} \tag{3}$$

where $f(\cdot)$, which models the maneuvering of the target, can be a linear or nonlinear function. The noise v_{k-1} is a zero-mean random variable with a fixed and known covariance matrix Q_v.

The global posterior distribution varies from time to time due to the removal of existing components (the non-determined components are confirmed to be clutter and the target components are confirmed to be vanishing targets), and addition of new components. At each time step, a number of judgement procedures based on the following principles are used to determine the structure of the global posterior distribution: a) A non-determined component is confirmed to be a target and kept; b) A non-determined component is confirmed to be clutter and removed; c) A target component is confirmed to be a vanishing target and removed; d) New components are generated at each time step.

3. AN EFFICIENT METHOD TO DISTINGUISH TARGET FROM CLUTTER

In this paper, an efficient method using multi-scan information is proposed to distinguish targets from clutter.

For each component P_i, its target probability $R_{i,k}$, the probability that component P_i being a true target at time step k, is calculated based on the measurements up to time step k (the detailed calculation procedure is in Section 3.1). A series of P_i's target probabilities from time step $k - L + 1$ to k are stored in a multi-scan sliding window with length L, $\{R_{i,k-L+1}, R_{i,k-L+2}, \ldots, R_{i,k}\}$. For the component corresponding to a target, most of its target probabilities in the sliding window are assigned with large values, provided the probability of target detection is moderate.

The history of each component's target probabilities within the sliding window could be used to judge whether the component is from a target or clutter: the component with large target probabilities at most of the scans is a true target; otherwise, the component corresponds to clutter. All we need to store is the history of each component's target probabilities within the sliding window, which reduces the memory size efficiently. The detailed procedure is listed as following:

1. Define T_{large} as the threshold of differentiating large target probability from small target probability.
2. Define $c = 0$ as a counter to store the number of large target probabilities for each sliding window.
3. For $j = 1$ to L, if $R_{i,k-L+j} > T_{\text{large}}$, $c = c + 1$.
4. Define L_{target} as the number of large target probabilities in the sliding window for the component corresponding to a true target. L_{target} is proportional to the detection probability P_D, and could be calculated as (4):
$$L_{\text{target}} = L \cdot P_D. \tag{4}$$
5. The judgement is made based on the following principle: if $c \geq L_{\text{target}}$, the component corresponds to a true target; otherwise, it corresponds to clutter.

3.1. Computation of the Target Probability Based on Multi-scan Information

The target probability $R_{i,k}$ is calculated based on multi-scan information. Firstly, the multiple scan joint association events [19] are examined in a multi-scan sliding window. The association event of component to measurement is defined as $\lambda_{k-L+1:k}$, where L denotes the length of the sliding window. The multiple scan joint association events are mutually exclusive, and they form a complete set $\Lambda_{k-L+1:k}$ [20]. $\lambda_{k-L+1:k}$ is composed by the association vectors at each scan in the sliding window, $\lambda_{k-L+1:k} = (\theta_{k-L+1}, \theta_{k-L+2}, \ldots, \theta_k)$. The elements of the association vector at time step k, $\theta_k = (\zeta_{1,k}, \ldots, \zeta_{j,k}, \ldots, \zeta_{N_k,k})$ are given by,

$$\zeta_{i,k} = \begin{cases} j \in \{1 \ldots M_k\}, \ldots \\ \text{if } P_i \text{ is related with measurement } z_j, \\ 0, \ldots \\ \text{if } P_i \text{ is related with none of measurements.} \end{cases} \tag{5}$$

where M_k denotes the number of measurements at time step k. The next step 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,

$$\begin{aligned} & p(\lambda_{k-L+1:k}|z_{1:k}) \\ \propto\ & p(z_k \ldots z_{k-L+1}|\lambda_{k-L+1:k}, z_{1:k-L})p(\lambda_{k-L+1:k}|z_{1:k-L}) \\ \propto\ & p(z_k \ldots z_{k-L+1}|\lambda_{k-L+1:k}, z_{1:k-L})p(\lambda_{k-L+1:k}), \end{aligned} \tag{6}$$

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,

$$\begin{aligned} & p(z_k \ldots z_{k-L+1}|\lambda_{k-L+1:k}, z_{1:k-L}) \\ =\ & \prod_{s=1}^{L} \left[\prod_{j=1}^{M_{k-L+s}} p(z_{j,k-L+s}|\lambda_{k-L+1:k}, z_{1:k-L}) \right]. \end{aligned} \tag{7}$$

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

$$\begin{aligned} & p(z_k \ldots z_{k-L+1}|\lambda_{k-L+1:k}, z_{1:k-L}) \\ =\ & \prod_{s=1}^{L} \left[\prod_{j=1}^{M_{k_s}} p(z_{j,k_s}|\lambda_{k-L+1:k}, z_{1:k-L}) \right] \\ =\ & \prod_{s=1}^{L} \left[\prod_{j \in I_{k_s}} p\left(z_{j(=\zeta_{i,k_s}),k_s}|x_{i,k_s}\right) \cdot \prod_{j \in I_{0,k_s}} p_{none}(z_{j,k_s}) \right] \\ =\ & \prod_{s=1}^{L} \left[\prod_{j \in I_{k_s}} p(z_{j(=\zeta_{i,k_s}),k_s}|x_{i,k_s}) \cdot (V)^{-C_{k_s}} \right], \end{aligned} \tag{8}$$

where I_{k_s} is the subsets of measurement indices corresponding to measurements from the existing components. For each $j \in I_{k_s}$, there would be one $i \in \{1, \ldots, N_{k_s}\}$ that satisfies $j = \zeta_{i,k_s}$. And I_{0,k_s} is the subsets of measurement indices corresponding to measurements from none of the existing components on scan k_s, which are named as unrelated measurements. p_{none} denotes the likelihood model for the unrelated measurements, which could be either from clutter or newly appeared targets. The likelihood model p_{none} is assumed to be uniform over the volume of the surveillance area V since we have no idea about its distribution at current time step. 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 unrelated measurements.

The joint association prior $p(\lambda_{k-L+1:k})$, can be calculated as in (9) according to [9, 21],

$$p(\lambda_{k-L+1:k}) = \prod\nolimits_{s=1}^{L} \left[\frac{F_{k_s}!\varepsilon}{N_{k_s}!} \prod\nolimits_{i=1}^{N_{k_s}} (P_D)^{\delta_i(\theta_{k_s})} (1-P_D)^{1-\delta_i(\theta_{k_s})} \right], \quad (9)$$

where ε is a "diffuse" prior [21] and P_D is the detection probability. $\delta_i(\theta_{k_s})$ is a binary variable and set to one if the ith component is assigned with a measurement in the event θ_{k_s}. F_{k_s} is the number of components which are not assigned with measurements in the event θ_{k_s}.

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

$$\begin{aligned} & p(\lambda_{k-L+1:k}|z_{1:k}) \\ \propto\ & p\left(\lambda_{k-L+1:k}\right) \prod\nolimits_{s=1}^{L} \left[\prod\nolimits_{j \in I_{k_s}} p(z_{j(=\zeta_{i,k_s}),k_s}|x_{i,k_s}) \cdot (V)^{-C_{k_s}} \right]. \quad (10) \end{aligned}$$

The posterior probability that the ith existing component is associated with the jth measurement at time step k, $p(\zeta_{i,k} = j|z_{1:k})$, is calculated by summing over the probabilities of the corresponding joint association events via (11),

$$p(\zeta_{i,k} = j|z_{1:k}) = \sum\nolimits_{\{\lambda_{k-L+1:k} \in \Lambda_{k-L+1:k} : \zeta_{i,k}=j\}} p(\lambda_{k-L+1:k}|z_{1:k}). \quad (11)$$

The target probability $R_{i,k}$ could be calculated via summing the probabilities that the ith existing component is associated with all the measurements in the validation gate of its track,

$$R_{i,k} = \Sigma_{j \in \{\mu(k,i,j)>0\}} p(\zeta_{i,k} = j|z_{1:k}) \quad (12)$$

where $\{\mu(k, i, j) > 0\}$ denotes the set of measurements falling in the validation gate of the track of component P_i at time step k.

4. NOVEL SAMPLING METHOD: THE COMBINATION OF THE LIKELIHOOD AND PRIOR SAMPLING

The posterior distribution of the multiple target state varies when tracking a varying number of targets. The number of modes of the posterior distribution may increase or decrease due to the appearance or disappearance of targets. New features of the posterior distribution may occur at each time step during the tracking process. The standard particle filter based on the prior sampling method can not cope with the new features, since it provides no opportunity to generate new values for unknown quantities after their initial generation. An additional procedure is needed to sample new particles to adapt to the new features of the posterior distribution.

A novel sampling algorithm which combines the likelihood sampling and prior sampling is proposed for the joint detection and tracking process in this paper. The likelihood sampling method draws new particles according to the most recent measurements. The new particles are then clustered to a number of new components, which capture the new features of the posterior distribution due to newly appeared targets or clutter. The prior sampling method ensures the existing components evolving according to the general dynamic model.

In the proposed sampling method, at time step $k-1$, the existing components (including target components and non-determined components) are evolving to time step k according to the general dynamic model. The track is extended for each of the existing components. The measurements at time step k are divided into two parts: those locating in the validation gates of the tracks of the existing components, and those are not. The likelihood sampling method is used to draw new particles based on the second part of measurements. The new particles are clustered to form the new components, which capture the new features of the posterior distribution.

In order to adapt to the new features, a number of particles are drawn according to the current measurements which are out of the validation gates of existing tracks. This reduce the number of particles largely compared to the methods that draw particles based on all the current measurements. The key idea is to sample x_k^i directly from the likelihood model, $\bar{q} = p(z_k|x_k)$. The importance weight of the sample x_k^i that is sampled from $\bar{q}$ can be written as [22]:

$$\begin{aligned} w_k^i &\propto [p(z_k|x_k)]^{-1} p\left(z_k|x_k^i\right) p\left(x_k^i|x_{k-1}^i\right) p\left(x_{k-1}^i|z_{1:k-1}\right) \\ &= p\left(x_k^i|x_{k-1}^i\right) p\left(x_{k-1}^i|z_{1:k-1}\right). \end{aligned} \tag{13}$$

Computing these importance weights is not trivial, since $p(x_{k-1}|z_{1:k-1})$ is represented by a set of samples. The strategy here is to employ a two-staged approach that first approximates $p(x_k^i|x_{k-1}^i)p(x_{k-1}^i|z_{1:k-1})$ and then use this approximate density to calculate the desired importance weights. The following procedure implements this importance sampler as shown in [22]:

(i) Generate a set of samples x_k^i, first by sampling from $p(x_{k-1}^i|z_{1:k-1})$

and then sampling from $p(x_k^i|x_{k-1}^i)$. Obviously, these samples approximate $p(x_k^i|x_{k-1}^i)p(x_{k-1}^i|z_{1:k-1})$.

(ii) Transform the resulting samples set into a kd-tree [23, 24]. The tree generalizes samples to arbitrary states, x_k^i, in state space, which is necessary to calculate the desired importance weights.

(iii) Lastly, sample x_k^i from the proposal distribution $p(z_k|x_k^i)$. Assign each sample with an importance weight that is proportional to its probability under the previously generated kd-tree.

The likelihood sampling method can be viewed as the logical "inverse" of the prior model sampling method. Rather than forward-guessing and then using the importance factors to adjust the likelihoods of hypothesis based on measurements, the likelihood sampling method guesses "backwards" from the measurements and adjusts the importance factors based on the belief $p(x_{k-1}|z_{1:k-1})$ [22].

5. JOINT DETECTION AND TRACKING PROCESS

The detection and tracking processes are integrated together in the proposed algorithm. During the joint detection and tracking process, it is required to maintain the track of existing targets as well as detect the newly appeared/disappeared targets. In the following sections, the processes of initialization, target appearance detection and target disappearance detection are introduced in Sections 5.1 to 5.3 respectively, and a general procedure for joint detection and tracking is listed in Section 5.4.

5.1. Initialization Stage

Initially at time step 0, NP particles are drawn from the likelihood function via the likelihood sampling method. The obtained particles are clustered to a number of initial particle clusters using K-means method. The initial particle clusters are converted into non-determined components and are evolving to time step 1 according to the general dynamic model. Individual track is formed for each of the non-determined components. The non-determined components are evolving from time step 1 to L with their target probabilities stored in corresponding sliding windows. At the end of the sliding window, the judgement procedures based on multi-scan information (proposed in Section 3) are used to determine the origin of each of the non-determined components: it is from a target or clutter. The target components are remained, and the clutter components are removed.

5.2. Newly Appeared Target Detection

At each time step, the measurements located in the validation gates of the tracks of existing components are used to update the existing tracks. The remaining measurements are thought to be related with the newly appeared targets or clutter. The likelihood sampling method is then used to draw new particles based on the remaining measurements. The particles are clustered to obtain new particle clusters, which correspond to new components. The new components are converted to the non-determined components and evolving to the next time step. After L scans, the judgement procedures based on multi-scan information as in Section 3 are used to determine either the non-determined component corresponds to a target or clutter.

5.3. Newly Disappeared Target Detection

For the detection of newly disappeared targets, the history of the existing target component's target probabilities stored in the sliding window is judged from time to time. If the target probability drops below the threshold T_{large} and remains at a small value for L_{target} scans (T_{large} and L_{target} are defined in Section 3), the target component could be treated as a vanishing target component and removed.

5.4. General Procedure for Joint Detection and Tracking

The general procedure for joint detection and tracking is listed in the following:

1. The existing components (including target components and non-determined components) are evolving from $k-1$ to k according to the general dynamic model. The track is extended for each of the existing components.

2. At time step k, the measurements located in the validation gates of the tracks of the existing components are used to update the existing tracks. The likelihood sampling method is then used to draw new particles based on the remaining measurements. The new particles are clustered to form the new components. The new components are then converted to the non-determined components.

3. The judgement procedures based on multi-scan information (Section 3) are used to determine the origin of each of the non-determined components which have evolved for L scans: it is from a target or clutter. The components confirmed to be clutter are removed.

4. Each of the target components from time step $k-1$ is judged based on the history information of its weights: the one with a sequence

of weights less than T_{large} for L_{target} scans are treated as a vanishing target and removed.

5. The remaining target components and un-determined components are evolving to time step $k+1$ according to the general dynamic model.

6. SIMULATION RESULTS AND ANALYSIS

In this section, the proposed multi-scan mixture particle filter algorithm is simulated to track a varying number of targets in a specific surveillance area. Two simulations are carried out to examine the performance of the proposed algorithm in the following areas: target detection, tracking, and data association. The first simulation is to detect and track twelve targets appearing and disappearing at different times in the surveillance area. The second is to detect and track four targets which moves closely to each other. All targets are synthesized using a near constant velocity dynamic model as in (14),

$$X_k = \Phi X_{k-1} + v_{k-1}, \tag{14}$$

where Φ is the transition matrix, and

$$\Phi = \begin{bmatrix} 1 & \Delta T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta T \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{15}$$

ΔT is the sampling interval. $X_k = [px, vx, py, vy]_k^T$ is the state vector; px and vx denote respectively the position and velocity of the moving object along the x axis of Cartesian frame; and, py and vy along the y axis. $v_k = [v_{px}, v_{vx}, v_{py}, v_{vy}]_k^T$ is the zero mean Gaussian white noise process with covariance Q: $E[v_k\ v_j^T] = Q\delta_{jk}$, where,

$$Q = \begin{bmatrix} \sigma_{px}^2 & 0 & 0 & 0 \\ 0 & \sigma_{vx}^2 & 0 & 0 \\ 0 & 0 & \sigma_{py}^2 & 0 \\ 0 & 0 & 0 & \sigma_{vy}^2 \end{bmatrix}. \tag{16}$$

A linear sensor is assumed with measurement equation,

$$Z_k = HX_k + n_k, \tag{17}$$

where,

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}. \tag{18}$$

The measurement noise $n_k = [n_{z_1}, v_{z_2}]_k^T$ is a zero mean Gaussian white noise process with variance R: $E[n_k\, n_j^T] = R\delta_{kj}$, where,

$$R = \begin{bmatrix} \sigma_{z_1}^2 & 0 \\ 0 & \sigma_{z_2}^2 \end{bmatrix}. \tag{19}$$

The area under surveillance is 2000 m long and 2000 m wide. The clutter measurements satisfied a Poisson distribution with density $3/\mathrm{m}^2$. The parameters for synthesising the simulation scenarios are listed in Table 1.

Simulation 1: Joint detection and tracking for multiple targets.

Twelve targets are considered in this simulation, which evolve independently according to the constant velocity model. The targets

Table 1. Simulation parameters.

Simulation Parameter	Value
Number of particles for each component (NP):	50
Sampling interval (ΔT):	0.1 sec
Variance matrix of process noise (Q):	diag{40 40 40 40}
Variance matrix of measurement noise (R):	diag{10 10}
Length of sliding window (L):	5
Detection probability (P_D):	0.8
Threshold T_{large}:	0.01

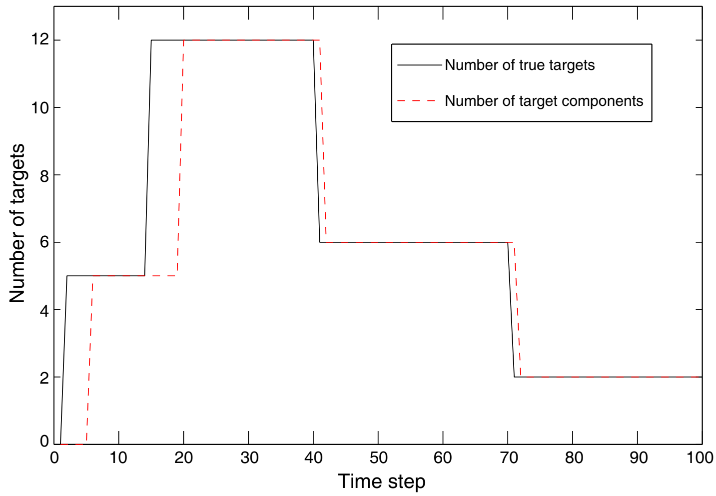

Figure 1. The estimate and actual number of targets at each time step for 12 targets.

appear and disappear at different times randomly (see Table 2). Figures 1 $\sim$ 2 show the results of the joint target detection and tracking. As shown in Figure 1, fixed delays incur when new target components are initiated and vanishing target components are removed. At other times, the number of target components is consistent with the number of true targets. The fixed lag for initiating the new target components equals the length of the sliding window (L), while the fixed lag for

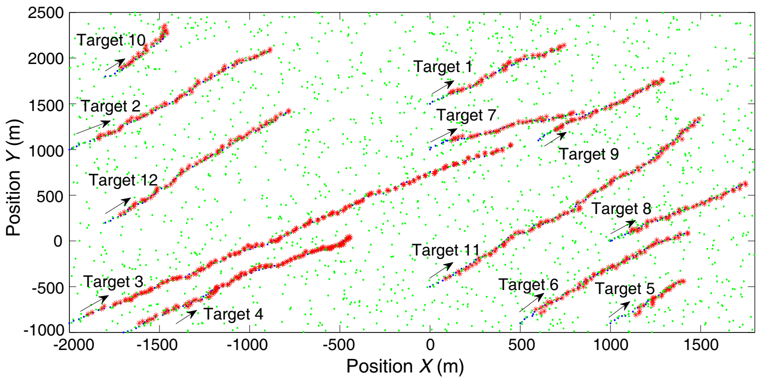

Figure 2. Synthesized scenario for 12 targets: Green dots '$\cdot$' represent measurements, blue dots '$\cdot$' represent true positions of targets at each time step, red asterisk '$*$' represent centers of target components.

Table 2. Target information for twelve targets.

Target No.	True Time Intervals	Detected Time Intervals	Initial Pos.	Initial Vel.
1	$[1, 40]$	$[6, 41]$	$[0, 1500]$	$[200, 200]$
2	$[15, 70]$	$[20, 71]$	$[-2000, 1000]$	$[200, 200]$
3	$[15, 100]$	$[20, \sim]$	$[-2000, -900]$	$[200, 200]$
4	$[1, 70]$	$[6, 71]$	$[-1700, -1000]$	$[180, 180]$
5	$[15, 40]$	$[20, 41]$	$[1000, -900]$	$[170, 170]$
6	$[15, 70]$	$[16, 71]$	$[500, -900]$	$[190, 190]$
7	$[1, 40]$	$[6, 41]$	$[0, 1000]$	$[170, 170]$
8	$[1, 40]$	$[6, 41]$	$[1000, 0]$	$[160, 160]$
9	$[1, 40]$	$[6, 41]$	$[600, 1100]$	$[160, 160]$
10	$[15, 40]$	$[20, 41]$	$[-1800, 1800]$	$[200, 200]$
11	$[15, 100]$	$[20, \sim]$	$[0, -500]$	$[190, 190]$
12	$[15, 70]$	$[20, 71]$	$[-1800, 200]$	$[180, 180]$

detecting the vanishing target components is set to one in order to detect the disappearance of targets fast.

In the proposed algorithm, the number of appeared/disappeared targets isn't limited to one. In Figure 1, seven targets appear at time step 15 simultaneously, and they are detected at time step 20. Similarly, six targets disappeared at time step 40, and they are detected at time step 41. The tracking performance of the proposed algorithm is demonstrated in Figure 2. It is shown that the proposed algorithm can track the multiple targets effectively as well as detect the appearance and disappearance of the targets.

Simulation 2: Joint detection and tracking for closely moving and crossing targets.

Four targets which moves closely are considered in this simulation.

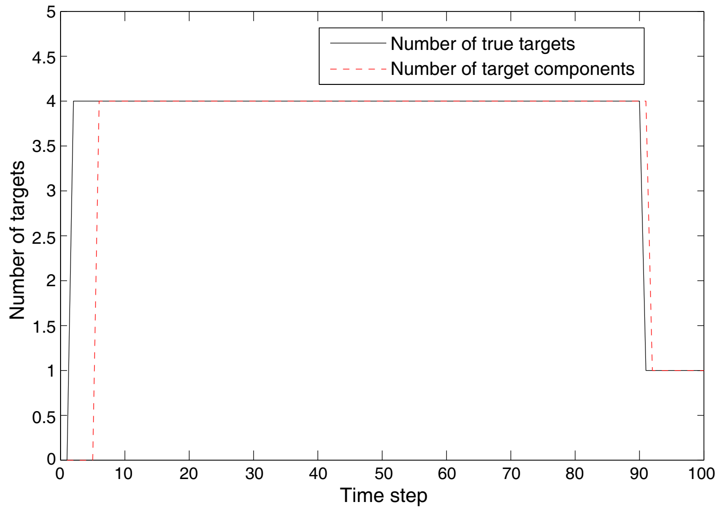

Figure 3. The estimate and actual number of targets at each time step for 4 targets.

Table 3. Target information for four targets.

Target No.	True Time Intervals	Detected Time Intervals	Initial Pos.	Initial Vel.
1	$[1, 90]$	$[6, 95]$	$[-1000, -700]$	$[180, 180]$
2	$[1, 90]$	$[6, 95]$	$[-500, -500]$	$[170, 170]$
3	$[1, 90]$	$[6, 95]$	$[0, -800]$	$[160, 160]$
4	$[1, 100]$	$[6, \sim]$	$[0, -1100]$	$[160, 160]$

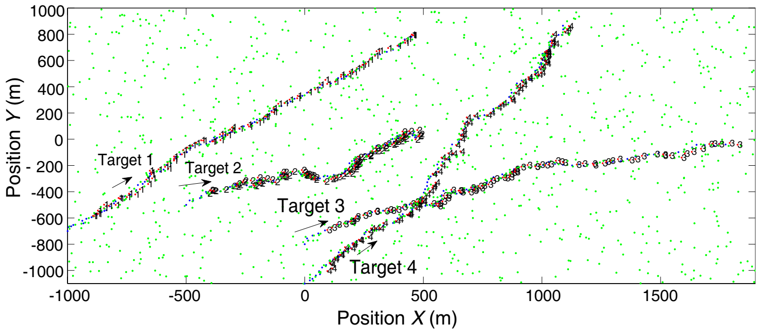

Figure 4. Synthesized scenario for 4 targets: Green dots '·' represent measurements, blue dots '·' represent true positions of targets at each time step, red dots '·' together with the corresponding numbers represent target component center and number.

The information of targets is listed in Table 3. Figures 3 $\sim$ 4 show the results of the joint target detection and tracking. In Figure 4, additional numbers are added to identify each target component for clarity. It is clear that all tracks follow the targets closely, and that those targets crossing each other are unambiguously resolved. This is verified that the closely moving targets could be distinguished based on multiple scan information though there is no individual data association procedure in the proposed method.

7. CONCLUSIONS

In the proposed multi-scan mixture particle filter method, a general global posterior distribution is adopted with each mode corresponding to either a target or clutter. In order to track a varying number of targets, a novel sampling method which combines the likelihood sampling and prior sampling is proposed to draw particles from the desired parts of the state space at each time step. Moreover, multiple scan information is incorporated to distinguish targets from clutter. The simulation results show that the proposed algorithm can effectively detect the apperaence/disappearence of the targets as well as track the existing target.

ACKNOWLEDGMENT

This work was supported by the Foundation for Innovative Research Groups of the National Natural Science Foundation of

China (61221063), and the Natural Science Foundations of China (No. 61104051, No. 61074176 and No. 61004087).

REFERENCES

1. Shi, Z.-G., Y. Zheng, X. Bian, and Z. Yu, "Threshold-based resampling for high-speed particle PHD filter," *Progress In Electromagnetics Research*, Vol. 136, 369–383, 2013.
2. Hong, S., L. Wang, Z.-G. Shi, and K. S. Chen, "Simplified particle PHD filter for multiple-target tracking: Algorithm and architecture," *Progress In Electromagnetics Research*, Vol. 120, 481–498, 2011.
3. Wang, X., J.-F. Chen, Z.-G. Shi, and K. S. Chen, "Fuzzy-control-based particle filter for maneuvering target tracking," *Progress In Electromagnetics Research*, Vol. 118, 1–15, 2011.
4. Chen, J.-F., Z.-G. Shi, S.-H. Hong, and K. S. Chen, "Grey prediction based particle filter for maneuvering target tracking," *Progress In Electromagnetics Research*, Vol. 93, 237–254, 2009.
5. Li, Y., Y. J. Gu, Z.-G. Shi, and K. S. Chen, "Robust adaptive beamforming based on particle filter with noise unknown," *Progress In Electromagnetics Research*, Vol. 90, 151–169, 2009.
6. Shi, Z.-G., S.-H. Hong, and K. S. Chen, "Tracking airborne targets hidden in blind doppler using current statistical model particle filter," *Progress In Electromagnetics Research*, Vol. 82, 227–240, 2008.
7. Oh, S., S. Russell, and S. Sastry, "Markov chain Monte Carlo data association for multi-target tracking," *IEEE Transactions on Automatic Control*, Vol. 54, No. 3, 481–497, 2009.
8. Reid, D., "An algorithm for tracking multiple targets," *IEEE Transactions on Automatic Control*, Vol. 24, 84–90, 1979.
9. Bar-Shalom, Y. and T. Fortmann, *Tracking and Data Association*, Academic Press, Orlando, FL, 1988.
10. Kastella, K. D., "A maximum likelihood estimator for report-to-track association," *Proc. SPIE*, 386–393, 1993.
11. Morelande, M., C. Kreucher, and K. Kastella, "A Bayesian approach to multiple target detection and tracking," *IEEE Transactions on Signal Processing*, Vol. 55, No. 5, 1589–1604, 2007.
12. De Maio, A., A. Farina, and G. Foglia, "Knowledge-aided Bayesian radar detectors & their application to live data," *IEEE*

Transactions on Aerospace and Electronic Systems, Vol. 46, No. 1, 170–183, Jan. 2010.

13. Jay, E., J. P. Ovarlez, D. Declercq, and P. Duvaut, "BORD: Bayesian optimum radar detector," *Signal Processing*, Vol. 83, No. 6, 1151–1162, Jun. 2003.
14. Vicen-Bueno, R., R. Carrasco-Alvarez, M. P. Jarabo-Amores, J. C. Nieto-Borge, and M. Rosa-Zurera, "Ship detection by different data selection templates and multilayer perceptrons from incoherent maritime radar data," *IET Radar, Sonar & Navigation*, Vol. 5, No. 2, 144–155, Feb. 2011.
15. Briones, J. C., B. Flores, and R. Cruz-Cano, "Multi-mode radar target detection and recognition using neural networks," *Int. J. Advanced Robotic Systems*, Vol. 9, No. 177, 1–9, Aug. 2012.
16. Vermaak, J., A. Doucet, and P. Pérez, "Maintaining multimodality through mixture tracking," *Proceedings of the Ninth IEEE International Conference on Computer Vision*, 2003.
17. Riaz, M. M. and A. Ghafoor, "Information theoretic criterion based clutter reduction for ground penetrating radar," *Progress In Electromagnetics Research B*, Vol. 45, 147–164, 2012.
18. Vicen-Bueno, R., R. Carrasco-Alvarez, M. Rosa-Zurera, and J. C. Nieto-Borge, "Sea clutter reduction and target enhancement by neural networks in a marine radar system," *Sensors*, Vol. 9, No. 3, 1913–1936, 2009.
19. Roecker, J. A., "Multiple scan joint probabilistic data association," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 31, 1204–1209, 1995.
20. Mušicki, D. and R. Evans, "Joint integrated probabilistic data association: JIPDA," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 40, No. 3, 1093–1099, 2004.
21. Chen, B. and J. K. Tugnait, "Tracking of multiple maneuvering targets in clutter using IMM/JPDA filtering and fixed-lag smoothing," *Automatica*, Vol. 37, 239–249, 2001.
22. Doucet, A., J. F. G. de Freitas, and N. J. Gordon, *Sequential Monte Carlo Methods in Practice*, Springer-Verlag, New York, 2001.
23. Bentley, J. L., "Multidimensional divide and conquer," *Communications of the ACM*, Vol. 23, No. 4, 1980.
24. Moore, A. W., "Efficient memory-based learning for robot control," Ph.D. Dissertation, Cambridge Univ., 1990.