

# A Particle Filter Track-before-detect Algorithm for Multi-Radar System

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**Abstract**—Current particle filter track-before-detect (PF-TBD) algorithms assume a single sensor system and a target being contained within the sensor detection coverage. In this paper, we develop PF-TBD for multiple asynchronous radar system. The radars in this system have different detection coverage, thus a target may move across the detection coverage of different radars (i.e. the target is not contained within the common detection coverage). For detecting dim target in this multi-radar system, a novel algorithm called classification PF-TBD (CPF-TBD) is proposed. It uses a classification criterion to divide the particles into two parts. This criterion is designed based on the detection coverage and the sampling rates of radars. According to the criterion, one part of the particles is used to estimate the target state, and the other part is used to preserve adequate particles in all radar detection coverage, which is conducive for next stage calculation. With this approach, the dim target can be centrally detected and tracked using all of the data, which is collected from asynchronous radars with different detection coverage. Simulation results show that CPF-TBD is able to produce higher accuracy compared with conventional PF-TBD.

**Index Terms**—Particle filter, track-before-detect, multi-radar, weak target, detection coverage, asynchronous.

## I. INTRODUCTION

The detection and tracking of weak targets is currently receiving more and more attention. Traditional strategies use a detect-then-track approach which forms target tracks based on the detections. The detections are obtained by applying a threshold on the output of the receiver [1], [2]. This is acceptable when the SNR (signal-to-noise ratio) is high. However, in low SNR environments, the signal amplitudes reflected from the target might not be strong enough to be detected. One possible approach is to lower the threshold, but a low threshold would give a high rate of false detections which cause tracker to form false tracks [3]. On the other hand, track-before-detect (TBD) techniques work with entire output of the receiver without applying a threshold and simultaneously detect and track target.

Because of reducing threshold loss, TBD techniques are efficient for weak targets detection [4].

Previously developed TBD techniques include Hough transform [5], dynamic programming [6] and particle filter [7], etc. For TBD problems, the main difficulty is that the signal amplitude is a non-linear and often non-Gaussian function of the target state [3], [8]. Since particle filter has the advantages of dealing with nonlinear/non-Gaussian problems [9], [10], recently it receives more and more attention when being used to perform track-before-detect recently [11]–[15]. In [13] a recursive TBD with target amplitude fluctuations is presented, while in [15] a multi-rate multiple model particle filter is derived by considering computational cost. For targets splitting situation, an extension of particle filter TBD algorithm is given in [1], but with an assumption that the maximum number of targets is known. In [12] a particle filter TBD is applied to detect extended target. However, the previously developed TBD methods take little account of the problem of a target cooperatively observed by multiple sensors. In [8] a developed TBD algorithm is proposed for multiple sensors, but the target is contained within common area of the sensors.

In this paper, we consider the problem of detecting and tracking dim target in multiple asynchronous radar system. The radar model refers to [1], [12]. For the radars have different detection coverage, the target may not be contained within common detection coverage, i.e. the target may move across the detection coverage of different radars. For example, suppose that a target disappears in the detection coverage of Radar A and appears in the detection coverage of Radar B. By particle filter TBD (PF-TBD), the dim target cannot be found existence or inexistence immediately, typically after several measurement scans [1], [3]. Thus, poor tracking estimation may be obtained when the target moves across the detection coverage. And when the target appears in the detection coverage of Radar B, it may be detected as a new target.

To solve this problem, we develop a new algorithm called classification PF-TBD (CPF-TBD) for multiple asynchronous radar system. It uses a classification criterion to divide the particles into two parts. Then different particle calculation methods are used according to the classification results. The

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criterion is designed based on the detection coverage and the sampling rates of radars. It ensures that one part of the particles is effective when being used to estimate the target existence (i.e. only the particles which are effective for estimation are selected), thus, the computation cost can be reduced. Furthermore, no matter whether the radars provide data or not currently, the criterion also ensures that the other part preserves adequate particles in all radar detection coverage after filtering (i.e. the particle diversity is preserved in all radar detection coverage). Thus, the phenomenon that most particles fall in some radars detection coverage can be eliminated. When the radars provide data in arbitrary order and the target moves across the detection coverage, adequate effective particles can be ensured for estimating the target existence and state. With this approach, the dim target can be centrally detected and tracked using all of the data available from asynchronous multiple radars with different detection coverage.

## II. SYSTEM SETUP

Suppose that there are  $L$  radars in the multi-radar system. Assume that any other targets are sufficiently well separated so that there will not be ambiguity between targets and that a single target analysis suffices. The radars collect data at different sampling rates and are not synchronized with each other. Meanwhile, the radars have different detection coverage and the target may move from some radars' detection coverage to the others'. The aim is to centrally detect and track the target using all of the data available from the radars.

Assume a sequence of data  $\{\mathbf{Z}_1, \dots, \mathbf{Z}_k, \dots\}$ , where  $\mathbf{Z}_k$  represents the measurements collected from multi-radar system at scan  $t_k$ . The measurements are time ordered, so  $t_{k-1} < t_k < t_{k+1}$ . These scans are arbitrary, but known. For the radars are not synchronized with each other, when the proportion of sampling rates is rational number, there exists a situation that multiple radar measurements are collected at the same time. Assume that there are  $D_k$  measurements collected at scan  $t_k$ , then the measurements  $\mathbf{Z}_k$  is given by

$$\mathbf{Z}_k = \{\mathbf{z}_{1,k}, \mathbf{z}_{2,k}, \dots, \mathbf{z}_{d,k}, \dots, \mathbf{z}_{D_k,k}\}, \quad (1)$$

where  $\mathbf{z}_{d,k}$  denotes the measurement collected from Radar  $d$ . The measurement is an image data.

Let the target state at scan  $t_k$  be denoted as  $\mathbf{s}_k$ . The state function can be formulated as

$$\mathbf{s}_k = f(\mathbf{s}_{k-1}, r_{k-1}, t_k, t_{k-1}) + \mathbf{g}(t_k, t_{k-1})\mathbf{w}_k, \quad (2)$$

where  $f(\cdot)$  is the system dynamics function and the statistic of the process noise  $\mathbf{w}_k$  is known.  $\mathbf{g}(t_k, t_{k-1})$  denotes the process noise input matrix. The discrete model state  $r_k$  represents one of the two hypotheses:

- $r_k = 0$ : there is no target exist;
- $r_k = 1$ : there is one target exist.

$r_k$  is represented by a Markov chain, which is formed as

$$p\{r_k = a | r_{k-1} = b\} = [\Psi(t_k)]_{ab}, \quad (3)$$

where  $\Psi(t_k)$  is Markov transition matrix and  $[\Psi(t_k)]_{ab}$  denotes the jump probability from model  $b$  to model  $a$ .

The measurement function of each radar is known, which is given by

$$\mathbf{z}_{d,k} = h_d(\mathbf{s}_k, r_k, \mathbf{v}_k), \quad (4)$$

where  $h_d(\cdot)$  denotes the non-linear measurement function of Radar  $d$ .  $\mathbf{v}_k$  represents the measurement noise and its statistic is known.

## III. MEASUREMENT MODEL

The measurement model refers to [1], [12] and it is given as follows.

One measurement  $\mathbf{z}_{d,k}$  is consisted of  $Nr_d \times Nb_d$  power measurements  $z_{d,k}^{ij}$ , where  $Nr_d$  and  $Nb_d$  are the number of range and bearing cells of Radar  $d$ . The power measurement per range-bearing cell is defined by

$$z_{d,k}^{ij} = |z_{A,d,k}^{ij}|^2, \quad (5)$$

where  $z_{A,d,k}^{ij}$  denotes the complex amplitude data, which is given by

$$z_{A,d,k} = \begin{cases} A_{d,k} h_{A,d}(\mathbf{s}_k, t_k) + n_d(t_k), & \text{target exists,} \\ n_d(t_k), & \text{no target,} \end{cases} \quad (6)$$

where  $A_{d,k} = \tilde{A}_{d,k} e^{i\varphi_{d,k}}$ ,  $\varphi_{d,k} \in (0, 2\pi)$  is the complex amplitude of the target. The noise  $n_d(t_k)$  is defined by

$$n_d(t_k) = n_{I,d}(t_k) + im_{Q,d}(t_k), \quad (7)$$

which is complex Gaussian distributed,  $n_{I,d}(t_k)$  and  $n_{Q,d}(t_k)$  are independent, zeros-mean and white Gaussian noise with variance  $\sigma_d^2$ . In (6),  $h_{A,d}(\mathbf{s}_k, t_k)$  is the reflection function, which is given for per range-bearing cell by

$$h_{A,d}^{ij}(\mathbf{s}_k, t_k) = \exp\left\{-\frac{(r_{d,i} - r_{d,k})^2}{2R_d} Lr_d - \frac{(b_{d,j} - b_{d,k})^2}{2B_d} Lb_d\right\}, \quad (8)$$

where  $i=1,2,\dots,Nr_d$ ,  $j=1,2,\dots,Nb_d$ .  $R_d$  and  $B_d$  represent constants related to the size of a range and bearing cell.  $Lr_d$  and  $Lb_d$  are constants of losses.  $r_{d,k}$  and  $b_{d,k}$  denote the position and bearing information of target and radar, which are given by:

$$r_{d,k} = \sqrt{(x_k - xp_d)^2 + (y_k - yp_d)^2}, \quad (9)$$

$$b_{d,k} = \arctan\left(\frac{y_k - yp_d}{x_k - xp_d}\right), \quad (10)$$

where  $(x_{p_d}, y_{p_d})$  represents the position of Radar  $d$  and  $(x_k, y_k)$  represents the target position state.

#### IV. CPF-TBD PROCEDURE

The CPF-TBD is proposed to detect and track dim target in asynchronous multi-radar system, and the radars have different detection coverage.

The CPF-TBD (block diagram shown in Fig. 1) uses a

classification criterion to divide the particles into two parts: Selected Part and Protected Part. Selected Part uses PF to estimate the existence of target, and Protected Part preserves particle diversity for the radars which are not sampling currently (i.e. adequate particles are preserved in all radar detection coverage). Assume an initial pdf (probability density function)  $p(\mathbf{s}_0, r_0)$  is given, CPF-TBD is carried out as follows.

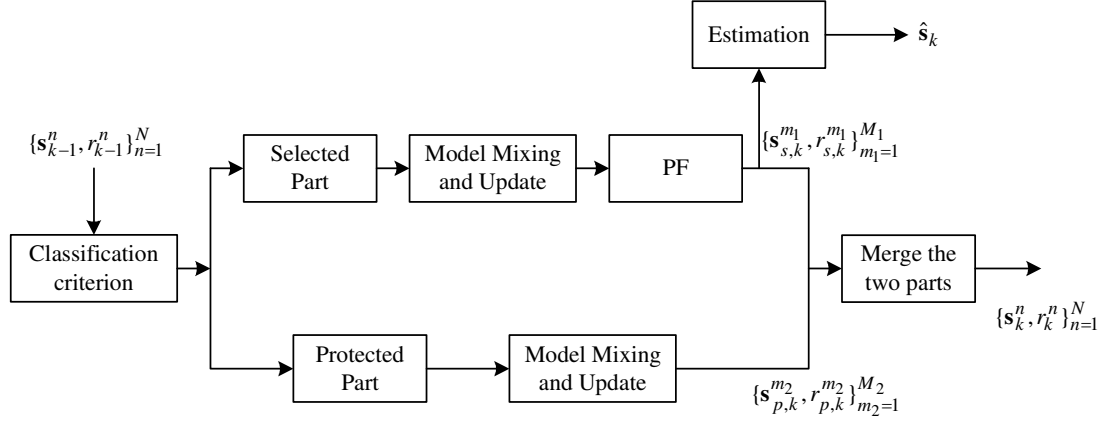


Fig. 1. CPF-TBD block diagram.

Step 1. Initialization. Draw  $N$  particles according to  $p(\mathbf{s}_0, r_0)$ , and obtain  $\{\mathbf{s}_0^n, r_0^n\}_{n=1}^N$ .

Step 2. Classification. Classify the particles into two parts according to the classification criterion. After classification, assume the numbers of the particles in Selected Part and Protected Part are  $M_1$  and  $M_2$  respectively. Then Selected Part and Protected Part are represented by  $\{\mathbf{s}_{s,k-1}^{m1}, r_{s,k-1}^{m1}\}_{m1=1}^{M1}$  and  $\{\mathbf{s}_{p,k-1}^{m2}, r_{p,k-1}^{m2}\}_{m2=1}^{M2}$  respectively.

Step 3. Model mixing and update. Perform model mixing according to the Markov transition matrix  $\Psi(t_k)$ . Perform particle state update using (2).

Step 4. PF. For Selected Part, given  $\mathbf{Z}_k$ , define the particle weights

$$\tilde{\omega}_k^{m1} \propto p(\mathbf{Z}_k | \mathbf{s}_{s,k}^{m1}, r_{s,k}^{m1}) \quad m_1 = 1, \dots, M_1 \quad (11)$$

Normalize the particle weights and resample  $M_1$  times from the Selected Part.

Step 5. Estimation. For Selected Part  $\{\mathbf{s}_{s,k}^{m1}, r_{s,k}^{m1}\}_{m1=1}^{M1}$ , assume the numbers of the particles corresponding to  $r_k = 1$  and  $r_k = 0$  are  $U_1$  and  $U_2$  respectively. Let  $p_{r_k=0}$  and  $p_{r_k=1}$  denote target inexistence probability and target existence probability respectively, which are formed as

$$p_{r_k=0} = U_1/M_1 \quad p_{r_k=1} = U_2/M_1. \quad (12)$$

If  $p_{r_k=1}$  exceeds threshold  $\lambda$ , the target is estimated to be exist. Then the target state estimation is obtained using

$$\hat{\mathbf{s}}_k = \frac{\sum_{m_1=1}^{M_1} \mathbf{s}_{s,k}^{m1} r_{s,k}^{m1}}{\sum_{m_1=1}^{M_1} r_{s,k}^{m1}}. \quad (13)$$

Step 6. Merge the two parts and obtain  $\{\mathbf{s}_k^n, r_k^n\}_{n=1}^N$ , then go to Step 2.

#### V. DESIGN OF CLASSIFICATION CRITERION

The classification criterion is used to divide the particles into two parts: Selected Part and Protected Part. According to the criterion, Selected Part is used to estimate the target state and Protected Part is used to preserve adequate particles in all radar detection coverage after filtering. Moreover, the scan when the particle is divided into Selected Part is defined as Selected Scan.

Suppose that there are  $D_k$  measurements collected from  $D_k$  radars at scan  $t_k$ , and let the detection coverage of Radar  $d$  ( $d = 1, 2, \dots, D_k$ ) be  $\Omega_d$ . The efficient coverage of the multi-radar system is the union of  $\Omega_d$ , i.e.

$$\Omega_k = \Omega_1 \cup \Omega_2 \cup \dots \cup \Omega_d \cup \dots \cup \Omega_{D_k} \quad (14)$$

where  $\Omega_k$  represents the efficient coverage of the multi-radar system. The aim is to determine whether the target exists in  $\Omega_k$  using the measurements collected at scan  $t_k$ . Thus, the particles outside  $\Omega_k$  cannot be effective when being used to estimate the target existence, but they can be used to preserve particle diversity for the radars which do not provide data at scan  $t_k$ .

Furthermore, let the sampling intervals of the radars be  $(T_1, T_2, \dots, T_L)$ , where  $L$  is the radar number. Then a time threshold  $T_{threshold}$  is given by

$$T_{threshold} = \max(T_1, T_2, \dots, T_L), \quad (15)$$

which is calculated as the maximum of all radar sampling intervals. Assume at scan  $t_{k-1}$ , we obtain particle set  $\{\mathbf{s}_{k-1}^n, r_{k-1}^n, st_{k-1}^n\}_{n=1}^N$  after filtering, where  $st_{k-1}^n$  stores the last Selected Scan of particle  $n$  (the scan when particle  $n$  is divided into Selected Part). Then at scan  $t_k$ , if the time interval satisfies (16)

$$t_k - st_{k-1}^n > T_{threshold}, \quad (16)$$

which means that particle  $n$  falls in none of multi-radar detection coverage, particle  $n$  will be useless for preserving the diversity.

According to the above description, the classification criterion is designed based on the detection coverage and the sampling intervals of different radars. For the particle set

$\{\mathbf{s}_{k-1}^n, r_{k-1}^n, st_{k-1}^n\}_{n=1}^N$ , two conditions are given.

Condition 1: the particle is in the efficient coverage  $\Omega_k$ .

Condition 2: the time interval that the particle is remained in Selected Part exceeds the time threshold  $T_{threshold}$ , i.e.

$$t_k - st_{k-1}^n > T_{threshold}.$$

The criterion is designed as following. If particle  $n$  satisfies either Condition 1 or Condition 2, it will be divided into Selected Part. Otherwise, it will be divided into Protected Part.

By this criterion, the CPF-TBD can centrally detect and track dim target in the multi-radar system. An example is given to describe the advantages of CPF-TBD in Fig. 2. According to Fig. 2, there are two radars with different detection coverage. Suppose that the measurements are collected from Radar A and Radar B at scan  $t_k$  and  $t_{k+1}$  respectively. When a target is at Position F at scan  $t_k$  (i.e. the measurement is collected from Radar A, and the target is in the detection coverage of Radar B but outside the detection coverage of Radar A), the Selected Part is effective for estimating target existence while the Protected Part is not. According to the criterion, only the particles in Selected Part are used for estimation, therefore, the computation cost can be reduced. Meanwhile, although Radar B doesn't provide measurement at scan  $t_k$ , the particles in Protected Part preserve diversity for Radar B, which ensures adequate particles are preserved in the detection coverage of Radar B. Thus, at next scan  $t_{k+1}$ , CPF-TBD can be more efficient to estimate target state when using the measurement collected from Radar B. Furthermore, when the target moves from Position F to H (i.e. the target moves from Radar B's detection coverage to Radar A's), CPF-TBD preserves the target detection and tracking results through the particles in Selected Part, and uses these information to estimate state when the target appears in the detection coverage of Radar A. Because of more information being used, the performance of CPF-TBD can be improved.

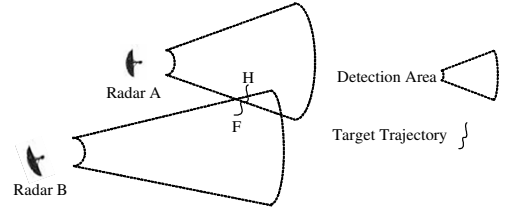


Fig. 2. Detection coverage of the two radars.

## VI. PARTICLE WEIGHT CALCULATION

The measurements collected at scan  $t_k$  are denoted as  $\mathbf{Z}_k = \{\mathbf{z}_{1,k}, \dots, \mathbf{z}_{d,k}, \dots, \mathbf{z}_{D_k,k}\}$ . These measurements, conditioned on the state  $\mathbf{s}_k$ , are assumed to be exponentially distributed [1]

$$p(z_{d,k}^{ij} | \mathbf{s}_k) = \frac{1}{\mu_0^{ij}} \exp\left\{-\frac{1}{\mu_0^{ij}} z_{d,k}^{ij}\right\}. \quad (17)$$

When  $r_k = 1$ ,  $\mu_0^{ij}$  is given by [1], [12]

$$\begin{aligned} \mu_0^{ij} &= E_{n_{I,d}, n_{Q,d}}(z_{d,k}^{ij}) = \\ &= E_{n_{I,d}, n_{Q,d}}\left(\left|\tilde{A}_{d,k}^2 e^{i\varphi_{d,k}} h_{A,d}^{ij}(s_k, t_k) + n_{I,d}(t_k) + m_{Q,d}(t_k)\right|^2\right) = \\ &= P_d \left(h_{A,d}^{ij}(s_k, t_k)\right)^2 + 2\sigma_d^2, \end{aligned} \quad (18)$$

with  $P_d = \tilde{A}_{d,k}^2$ .

When  $r_k = 0$ ,  $\mu_0^{ij}$  is given by

$$\mu_0^{ij} = E_{n_{I,d}, n_{Q,d}}(z_{d,k}^{ij}) = 2\sigma_d^2. \quad (19)$$

Suppose that the noise is independent from cell to cell and the measurements are independent, we obtain

$$p(\mathbf{Z}_k | \mathbf{s}_k) = \prod_{d=1}^{D_k} p(\mathbf{z}_{d,k} | \mathbf{s}_k) = \prod_{d=1}^{D_k} \prod_{i=1}^{N_{r_d}} \prod_{j=1}^{N_{b_d}} p(z_{d,k}^{ij} | \mathbf{s}_k). \quad (20)$$

## VII. SIMULATION COMPARISON

In this section, we give a demonstration of CPF-TBD that is capable of detecting weak target in multi-radar system. In the simulation, CT (Coordinate turn) model is used to describe the target maneuvering moving motion. The target state is defined as  $\mathbf{s}_k = [x, y, \dot{x}, \dot{y}, \omega]$ , where  $(x, y)$  and  $(\dot{x}, \dot{y})$  denote the target positions and velocities in x-y plane respectively.  $\omega$  is the turn rate. The state function and the process input matrix in (2) are given by [1], [12]:

$$f(\mathbf{s}_{k-1}, r_{k-1}, t_k, t_{k-1}) = \begin{pmatrix} 1 & \frac{\sin \omega \tau}{\omega} & 0 & -\frac{1 - \cos \omega \tau}{\omega} & 0 \\ 0 & \cos \omega \tau & 0 & -\sin \omega \tau & 0 \\ 0 & \frac{1 - \cos \omega \tau}{\omega} & 1 & \frac{\sin \omega \tau}{\omega} & 0 \\ 0 & \sin \omega \tau & 0 & \cos \omega \tau & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \mathbf{s}_{k-1}, \quad (21)$$

$$\mathbf{g}(t_k, t_{k-1}) = \begin{pmatrix} (a_{x,\max}/6)\tau^2 & 0 & 0 \\ 0 & (a_{y,\max}/6)\tau^2 & 0 \\ a_{x,\max}\tau/3 & 0 & 0 \\ 0 & a_{y,\max}\tau/3 & 0 \\ 0 & 0 & a_{\omega,\max}\tau \end{pmatrix}, \quad (22)$$

where  $\tau = t_k - t_{k-1}$ .  $a_{x,\max}$ ,  $a_{y,\max}$  and  $a_{\omega,\max}$  represent maximum accelerations.

In this scenario, initially there is no target presents. The target appears after 5s at a position of (13.3,0.4) km and with velocity of  $(-0.2,0.29)$  km/s, and the initial turn rate is 0.12 rad/s. At  $t = 40$ s the target disappears.  $a_{x,\max} = a_{y,\max} = 0.015$  m/s<sup>2</sup> and  $a_{\omega,\max} = 0.005$  rad/s<sup>2</sup>. The process noise is assumed to be standard white Gaussian noise. The total simulation time is 50 seconds.

We consider two radars in the multi-radar system here, i.e.  $L = 2$ . The sampling intervals of the two radars are  $T_1 = 1$  s and  $T_2 = 1.4$  s respectively. For the two radars, we consider range cells in the interval [5,15] km and bearing cells in the interval  $[-15^\circ, 15^\circ]$ , then  $Nr_l \times Nb_l$  ( $l=1,2$ ) cells are obtained, where  $Nr_1 = 40$ ,  $Nb_1 = 25$ ,  $Nr_2 = 50$ ,  $Nb_2 = 30$ . The positions of the two radars are  $(-1,4)$  km and  $(1,0)$  km respectively. Seen from the above, Radar 2 has longer sampling interval and higher resolution.

Fig. 3 shows the target trajectory and the detection coverage of the two radars. In Fig. 3, "o" denotes the target position when Radar 1 provides measurement, and "\*" denotes the target position when Radar 2 provides measurement. The regions surrounded by the solid lines are the radar detection coverage. Inspection of Fig. 3 shows that the target firstly appears in the detection coverage of Radar 2. In the time interval [17.4,31.5] s, the target is in the detection coverage of Radar 1. In [5,9,8] s and [33.6,40] s, the target is in the detection coverage of Radar 2. And in [9.8,17.4] s and [31.5,33.6] s, the target is in the common coverage of the two radars.

In this simulation, two measurements are collected at  $t = 21$  s. Let  $P_1 = P_2 = 2.5$  and  $\sigma_1 = \sigma_2 = 0.5$ , i.e.  $SNR = 7$  dB, Fig. 4 shows the two radar measurements. Inspection of Fig. 4 show that the target signal is drown in the noise.

In this simulation, the performance of CPF-TBD is compared with conventional PF-TBD. For PF-TBD considers a single target, we use PF-TBD to process the measurements collected from Radar 1, likewise, we use PF-TBD to process the measurements collected from Radar 2. After that, two estimation results are obtained respectively. If one target existence probability exceeds threshold  $\lambda$  in two successive scan, only this existence probability will be used to compare the existence probability obtained by CPF-TBD. Meanwhile, if the two radars provide measurements at the same scan, two RMSE (root mean square error) of the target will be obtained, and the smaller RMSE will be used to compare the RMSE

obtained by CPF-TBD.

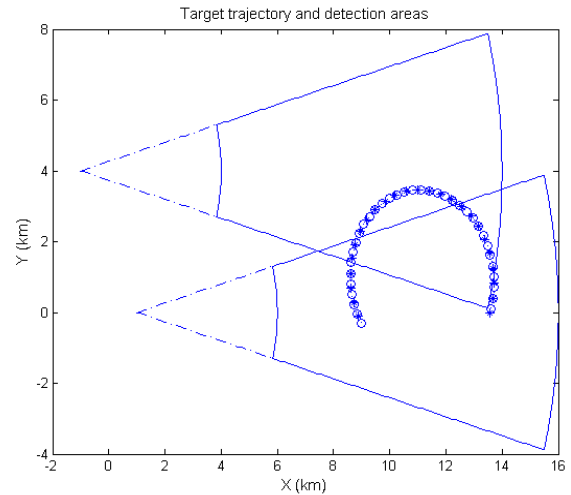


Fig. 3. Target trajectory and radar detection coverage.

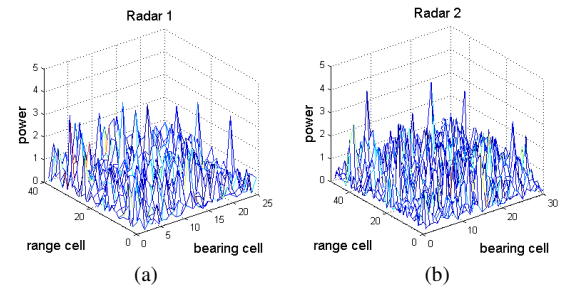


Fig. 4. Measurements collected from the two radars at  $t = 21$  s.

In the simulation, the particle number is  $N = 2000$  particles. The transition probability matrix is  $\Psi(t_k) = \begin{pmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{pmatrix}$ . The threshold  $\lambda$  is set to be 0.6.

After 100 Monte Carlo runs, Fig. 5 shows the comparison results of target existence probability, and Fig. 6 shows the RMSE comparison results.

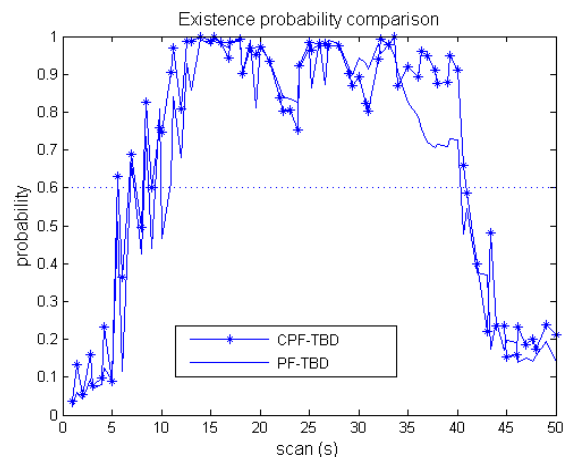


Fig. 5. Target existence probability comparison.

Inspection of Fig. 5 and Fig. 6 shows that CPF-TBD produces higher existence probability and tracking accuracy than PF-TBD, and when a target moves out of one radar's detection coverage but it moves into the other's, the

performance of CPF-TBD is significantly improved.

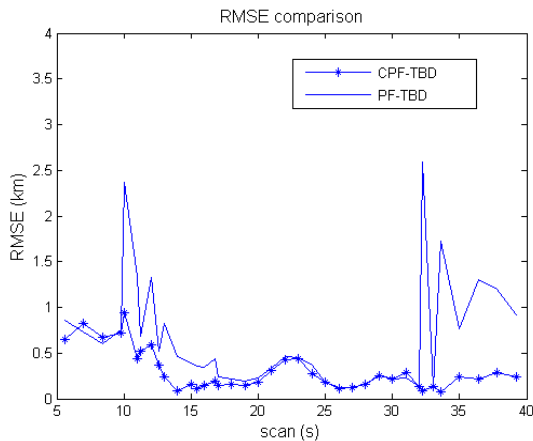


Fig. 6. RMSE comparison results.

Compared with conventional PF-TBD, CPF-TBD has advantages when a target moves across the radar detection coverage. In the simulation, when a target moves out of the one radar's detection coverage, the target detection and tracking results are preserved through the particles in Selected Part. Then when the target appears in the detection coverage of the other radar, CPF-TBD uses the information preserved in Selected Part to estimate the target appearance and state. Because of more information being used, according to Fig. 5 and 6, CPF-TBD performs more efficiency than conventional PF-TBD, especially when the target moves across the radar detection coverage.

## VIII. CONCLUSIONS

For detecting and tracking dim targets in asynchronous multi-radar system, a novel algorithm called classification PF-TBD (CPF-TBD) is proposed in this paper. The algorithm uses a classification criterion to divide the particles into two parts, and different calculation methods are used according to the classification results. The criterion is designed based on the detection coverage and the sampling rates of radars. It ensures that one part of the particles is effective when being used to estimate the target existence and state. Meanwhile, it also ensures that the other part of the particles preserves adequate particles in all radar detection coverage after filtering, which is conducive for next stage calculation. Simulation results show that CPF-TBD works well to detect target using all of the data, which is collected from asynchronous radars with different detection coverage. And compared with conventional PF-TBD, the detection probability and tracking accuracy of CPF-TBD are improved, especially when a target moves across the radar detection coverage.

Conventional PF-TBD considers a single target situation and it cannot be used to detect multi-target [3]. Some extended PF-TBD algorithms for multi-target detection are proposed recently but with too much limitation. In this paper, we assume that any other targets are sufficiently well separated, thus a single target analysis suffices. However, many practical situations require the detection of multiple targets. Therefore, further work will mainly focus on how to detect and track multi-target in asynchronous multi-radar

system.

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