Chinese Journal of Electronics
Vol.18, No.1, Jan. 2009

Particle Filter Based Track-before-detect Algorithm for Over-the-horizon Radar Target Detection and Tracking*

SU Hongtao, SHUI Penglang, LIU Hongwei and BAO Zheng

(*National Laboratory of Radar Signal Processing, Xidian University, Xi'an 710071, China*)

Abstract — A particle filter based Track-before-detect (TBD) algorithm for Over-the-horizon radar (OTHR) target detection and tracking is proposed in this paper. In the TBD algorithm the unthresholded measurements are integrated over time, thus it can potentially detect and track targets with a much lower signal-to-noise ratio than conventional methods. Such a characteristic make the TBD technique adequate for OTHR target detection and tracking. The performance of the proposed algorithm employs different unthresholded measurements, such as complex measurements, amplitude measurements and power measurements, are compared and discussed. Simulation results show that the proposed algorithm is capable to detect and track dim targets for OTHR and the amplitude measurements are preferred for the proposed algorithm.

Key words — Track-before-detect, Over-the-horizon radar, Particle filter.

I. Introduction

High frequency (HF) sky wave Over-the-horizon radar (OTHR) operates in the HF band ($3-30$MHz), which can provide over the horizon detection of targets on large surveillance areas[1]. Due to the resonant scattering, the OTHR has the potential ability to detect stealth targets. In addition, the long wavelengths characteristic provides a means for sea-state monitoring[2]. However, the look-down operation mode also brings great challenges to the target detection of the OTHR. The undesired echoes arose from the ground or ocean might be $40-80$dB greater than that of the targets. Thus, Doppler processing is necessary in OTHR system to extract moving targets from the undesired background clutter. Improved Signal to noise ratio (SNR) can be achieved by employing long Coherent integration time (CIT), but the coherent integration time is limited by several factors such as ionosphere stability, target motion characteristics, radar revisit rates, etc. Accordingly, low SNR moving target detection is a difficult problem for OTHR.

Track before detect (TBD) is a procedure where a number of scans are processed and after that the estimated target track is returned at the same time as the detection is declared[3−7]. In contrast to classical radar tracking, in TBD a number of unthresholded measurements integrated over time are used. Thus, the detection performance of TBD is improved when compared to that of the conventional one.

An efficient method to implement TBD algorithm is based on a particle filter approach[4−7], which is a technique for implementing a recursive Bayesian filter by Monte carlo (MC) simulations[8−11]. The key idea is to represent the required posterior Probability density function (PDF) by a set of random samples with associated weights. As the number of samples becomes large, they effectively provide an equivalent representation of the required posterior PDF. Different measurements, such as complex measurements[6], amplitude measurements[7] and power measurements[5], have been used in the particle filter based TBD algorithms. However, the performance of the particle filter based TBD algorithm employs different measurements have not been compared and discussed before.

In this paper, a particle filter based TBD algorithm for OTHR dim target detection and tracking is presented. Furthermore, the performance of the different unthresholded measurements are used in the proposed algorithm are compared and discussed.

II. System Dynamic and Measurement Models

1. System dynamic model

Since the typical range resolution of an OTHR is 15-30km, targets of interest to an OTHR cannot travel across one range bin during one CIT. Therefore, in our application, only the velocity and the acceleration are involved in target state vector. Moreover the unknown target echo amplitude is also incorporated. In conventional Doppler processing target Doppler frequency is usually assumed to be a constant during one CIT. However, target Doppler frequency due to target motion is often time varying, which may cause integration losses in the Doppler processing. To alleviate the effect of the time varying Doppler frequency the measurement sequence of one range

*Manuscript Received Nov. 2007; Accepted Sept. 2008.

bin is divided into K segments, each of which has a CIT of T_k and T_k is selected so that the Doppler frequency in each segment can be regarded as approximately constant. The target echo amplitude is considered approximately constant in each segment but it fluctuates from one segment to other. In the application under consideration, the target state vector is defined as

$$\boldsymbol{x}_k = [\, f_d^k \quad f_{da}^k \quad A_k \,]^T \tag{1}$$

where f_d^k denotes target Doppler frequency in segment k, f_{da}^k denotes target Doppler frequency increment due to target acceleration, A_k denotes target echo amplitude in segment k. In our application, it assumed that the target undergoes a constant acceleration motion from segment to segment. Since the acceleration is never constant, its slight changes can be modeled by zero mean white noise. Besides, the target echo amplitude fluctuation from segment to segment is also modeled as a random walk. Thus, the system dynamic model can be defined as

$$\boldsymbol{x}_k = \begin{bmatrix} 1 & T_{k-1} & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \boldsymbol{x}_{k-1} + \begin{bmatrix} 0.5T_{k-1}^2 & 0 \\ T_{k-1} & 0 \\ 0 & 1 \end{bmatrix} \boldsymbol{v}_{k-1} \tag{2}$$

where $\boldsymbol{v}_{k-1} = \begin{bmatrix} \boldsymbol{v}_{k-1}^{(1)} \\ \boldsymbol{v}_{k-1}^{(2)} \end{bmatrix}$ is the process noise vector, $\boldsymbol{v}_{k-1}^{(1)}$ denotes the target acceleration change due to the target Doppler frequency variation, $\boldsymbol{v}_{k-1}^{(2)}$ denotes the fluctuation of the target echo amplitude. Furthermore, $\boldsymbol{v}_{k-1}^{(1)}$ and $\boldsymbol{v}_{k-1}^{(2)}$ are mutually independent, zero mean white noise, with variances $\sigma_{k(1)}^2$ and $\sigma_{k(2)}^2$, respectively. Because the target can be present or absent in the measurement at a time instant k, target presence variable E_k is modeled by a two state Markov chain that is $E_k \in \{0,1\}$. Where 0 denotes the event that a target is absent, while 1 denotes a target is present[6]. Furthermore, both the probability of transition from absent to present *i.e.*, 'birth of the target', $\Pr\{E_k = 1|E_{k-1} = 0\} = P_b$ and transition from present to absent *i.e.*, 'death of target', $\Pr\{E_k = 0|E_{k-1} = 1\} = P_d$ are assumed to be known. The transitional Markov matrix is given by

$$\prod = \begin{bmatrix} 1 - P_b & P_b \\ P_d & 1 - P_d \end{bmatrix} \tag{3}$$

2. Measurement model

The receiver output signal sequence of an OTHR system in the segment k is

$$s_k(n) = A_k e^{j2\pi f_d^k n + \phi_k} + n_k(n), \quad n = 0, 1, \cdots, N-1, \qquad k = 1, 2, \cdots, K \tag{4}$$

where ϕ_k is some arbitrary phase and $n_k(n)$ is the background noise. The windowed Doppler processing is

$$z_k(l) = \sum_{n=0}^{N-1} s_k(n) \cdot w_n \cdot e^{-j2\pi \frac{nl}{N}}, \quad l = 0, 1, N-1, \qquad k = 1, 2, \cdots, K \tag{5}$$

where w_n is window function, $z_k(l)$ is the output signal of the windowed Doppler processing at frequency bin l in segment k. The signal in each Doppler frequency bin can be written as

$$z_k(l) = \begin{cases} h(S_k(l), N_k(l)), & E_k = 1 \\ h(0, N_k(l)), & E_k = 0 \end{cases} \tag{6}$$

where $h(\cdot,\cdot)$ denotes the windowed Doppler processing, the target echo signal and the background noise after windowed Doppler processing is $S_k(l)$ and $N_k(l)$, respectively. According to the central limit theory[12], the background noise obeys complex Gaussian distribution. Without loss of generality, we further assume that it has zero mean. Then $N_k(l)$ is also a zero mean i.i.d. complex variable distributed according to Gaussian distribution. By supposing it has a variance $2\sigma_N^2$, the signal likelihood functions of a Doppler frequency bin are[13]

$$\begin{aligned} p(z_k(l)|\boldsymbol{x}_k, E_k = 1) = & N(real(z_k(l)), real(S_k(l), \sigma_N^2) \\ & \cdot N(imag(z_k(l)), imag(S_k(l)), \sigma_N^2) \end{aligned} \tag{7a}$$

$$\begin{aligned} p(z_k(l)|E_k = 0) = & N(real(z_k(l)), 0, \sigma_N^2) \\ & \cdot N(imag(z_k(l)), 0, \sigma_N^2) \end{aligned} \tag{7b}$$

where $real(\cdot)$ and $imag(\cdot)$ denotes real and imaginary part of the signal, $N(\boldsymbol{m}, \boldsymbol{P})$ is a Gaussian PDF with mean $\boldsymbol{m}$, and covariance $\boldsymbol{P}$.

The amplitude signal in a Doppler frequency bin has a Ricean distribution while a target is present and a Rayleigh distribution while a target is absent. The corresponding likelihood functions are[13]

$$\begin{aligned} p(|z_k(l)|\|\boldsymbol{x}_k, E_k = 1) = & \frac{|z_k(l)|}{\sigma_N^2} \exp\left(- \frac{|z_k(l)|^2 + |S_k(l)|^2}{2\sigma_N^2} \right) \\ & \cdot I_0\left(\frac{|S_k(l)\|z_k(l)|}{\sigma_N^2} \right) \end{aligned} \tag{8a}$$

$$p(|z_k(l)\|E_k = 0) = \frac{|z_k(l)|}{\sigma_N^2} e^{-|z_k(l)|^2/2\sigma_N^2} \tag{8b}$$

where $|\cdot|$ denotes the amplitude of the signal, $I_0(\cdot)$ denotes the modified Bessel function of order zero.

The power of the signal with and without a target in a Doppler frequency bin results in two other corresponding likelihood functions. They are[13]

$$\begin{aligned} p(|z_k(l)|^2|\boldsymbol{x}_k, E_k = 1) = & \frac{1}{\sigma_N^2} \cdot \exp\left(- \frac{|z_k(l)|^2 + |S_k(l)|^2}{2\sigma_N^2} \right) \\ & \cdot I_0\left(\frac{|S_k(l)\|z_k(l)|}{\sigma_N^2} \right) \end{aligned} \tag{9a}$$

$$p(|z_k(l)|^2|E_k = 0) = \frac{1}{\sigma_N^2} e^{-|z_k(l)|^2/2\sigma_N^2} \tag{9b}$$

where $|\cdot|^2$ denotes the power of the signal.

The complex measurement at time instant k is defined as

$$\boldsymbol{z}_k = [z_k(0), z_k(1), \cdots, z_k(N-1)] \tag{10}$$

Furthermore, we define amplitude measurement and power measurement at time instant k as

$$|\boldsymbol{z}_k| = [|z_k(0)|, |z_k(1)|, \cdots, |z_k(N-1)|]$$

and

$$|\boldsymbol{z}_k|^2 = [|z_k(0)|^2, |z_k(1)|^2, \cdots, |z_k(N-1)|^2$$

respectively.

Since the noise in each Doppler frequency bin is assumed to be independent, then the likelihood function of the measurement is a product over all contributions from each Doppler frequency bin. Due to the windowing of the Doppler processing, the target (if present) power will spread into the vicinity bins of its location. Let's $C(\boldsymbol{x}_k)$ denote the bins affected by the target, then the likelihood functions of complex measurement can be approximated as follows[6]

$$p(\boldsymbol{z}_k|\boldsymbol{x}_k, E_k=1) \approx \prod_{l\in C(x_k)} p(z_k(l)|x_k, E_k=1) \cdot \prod_{l\notin C(x_k)} p(z_k(l)|E_k=0) \tag{11a}$$

$$p(\boldsymbol{z}_k|E_k=0) = \prod_{l=1}^{N} p(z_k(l)|E_k=0) \tag{11b}$$

The likelihood functions of the amplitude measurement and the power measurement can be derived in the same way as given by Eqs.(11a) and (11b).

III. Particle Filter Based TBD Algorithm

1. The SIR filter based TBD algorithm

There are various algorithms to implement simulation based recursive Bayesian estimation[7−11]. The SIR filter has the advantage of easily sampling because it utilizes the prior probability density function as importance density. In addition, the important weights of the SIR filter are easily evaluated. Since the unnormalised important weights are proportional to the likelihood functions, using the likelihood ratios as unnormalised weights will have no effects on the performance of the SIR filter. The likelihood ratios of the complex measurement, amplitude measurement and power measurement can be computed as

$$L(\boldsymbol{z}_k|\boldsymbol{x}_k, E_k=1) = \frac{p(\boldsymbol{z}_k|\boldsymbol{x}_k, E_k=1)}{p(\boldsymbol{z}_k|E_k=0)} \approx \prod_{l\in C_i(x_k)} \frac{p(z_k(l)|\boldsymbol{x}_k, E_k=1)}{p(z_k(l)|E_k=0)} \tag{12a}$$

$$L(\boldsymbol{z}_k|E_k=0) = \frac{p(\boldsymbol{z}_k|E_k=0)}{p(\boldsymbol{z}_k|E_k=0)} = 1 \tag{12b}$$

$$L(|\boldsymbol{z}_k||\boldsymbol{x}_k, E_k=1) \approx \prod_{l\in C_i(x_k)} e^{-|S_k(l)|^2/2\sigma_N^2} \cdot I_0\left(\frac{|S_k(l)||z_k(l)|}{\sigma_N^2}\right) \tag{13a}$$

$$L(|\boldsymbol{z}_k||E_k=0) = 1 \tag{13b}$$

$$L(|\boldsymbol{z}_k|^2|\boldsymbol{x}_k, E_k=1) \approx \prod_{l\in C_i(x_k)} e^{-|S_k(l)|^2/2\sigma_N^2} \cdot I_0\left(\frac{|S_k(l)||z_k(l)|}{\sigma_N^2}\right) \tag{14a}$$

$$L(|\boldsymbol{z}_k|^2|E_k=0) = 1 \tag{14b}$$

Utilizing the likelihood ratios as the unnormalised weights of the SIR filter, a pseudo description of the proposed algorithm is given as follows

(1) Set $k=1$, generate N_s samples $\{E_1^i\}_{i=1}^{N_s}$ from $\Pr(E_1=1)$

If $E_1^i=1$, Generate $\boldsymbol{x}_1^i$ from $p(\boldsymbol{x}_1|\boldsymbol{z}_1)$

If $E_1^i=0$, $\boldsymbol{x}_1^i$ is undefined

(2) Generate $\{E_k^{\cdot i}\}_{i=1}^{N_s}$ on the basis of $\{E_{k-1}^i\}_{i=1}^{N_s}$ and $\prod$

(3) for $i=1:N_s$

If $E_{k-1}^i=0$ and $E_k^{\cdot i}=1$

Generate $x_k^{\cdot i}$ from $q(\boldsymbol{x}_k|\boldsymbol{z}_k)$

If $E_{k-1}^i=1$ and $E_k^{\cdot i}=1$

Generate $\boldsymbol{x}_k^{\cdot i}$ from the prior density $p(\boldsymbol{x}_k|\boldsymbol{x}_{k-1}^{\cdot i})$

(4) Compute the likelihood ratio weights $\{w_k^i\}_{i=1}^{N_s}$

(5) Normalise the weights $\left\{\tilde{w}_k^i = w_k^i \Big/ \sum_{i=1}^{N_s} w_k^i\right\}_{i=1}^{N_s}$

(6) Generate a new set of samples $\{\boldsymbol{x}_k^i, E_k^i\}_{i=1}^{N_s}$ by resampling with replacement N_s times from the discrete set $\{\boldsymbol{x}_k^{\cdot i}, E_k^{\cdot i}\}_{i=1}^{N_s}$ where $\Pr\{\boldsymbol{x}_k^j=\boldsymbol{x}_k^{\cdot i}\}=\tilde{w}_k^i$

(7) Increase k and iterate to step (2)

In the above algorithm, the newborn particles, which is characterized by the transition from $E_{k-1}^i=0$ to $E_k^i=1$, are draw from $q(\boldsymbol{x}_k|\boldsymbol{z}_k)$. Under the assumption that the present of a target will always disturb the underlying noise, the proposal density $q(\boldsymbol{x}_k|\boldsymbol{z}_k)$ is obtained as follows. For target Doppler frequency component, uniform samples are drawn from bins in the measurement which have amplitude that exceeds a predefined threshold. For target Doppler frequency increment component, the proposal density is uniform over $[-f_{da}^{\max}, f_{da}^{\max}]$, where $f_{da}^{\max}$ is the maximum target Doppler frequency increment. Also the proposal density of target echo amplitude component is taken to be uniform over $[A_k^{\min}, A_k^{\max}]$, where $A_k^{\min}$ and $A_k^{\max}$ is the minimum and maximum target echo amplitude, respectively.

The joint posterior PDF at time k, namely $p(\boldsymbol{x}_k, E_k|\boldsymbol{z}_k)$, is characterised by $\{\boldsymbol{x}_k^{\cdot i}, E_k^{\cdot i}, \tilde{w}_k^i\}_{i=1}^{N_s}$. Since the accuracy of any estimate of a function of the distribution can only decrease as a result of the resampling[8], the set of samples before resampling to those after resampling is preferred. Therefore the posterior probability of target existence at time k, namely $p_{E_k} \triangleq p(E_k|\boldsymbol{z}_k)$, can be computed as

$$\hat{p}_{E_k} = \textstyle\sum_{i=1}^{N_s} E_k^{\cdot i}\cdot\tilde{w}_k^i \tag{15}$$

When target existence probability $\hat{p}_{E_k}$ excesses a predefined threshold target presence is declared.

Once the joint posterior PDF at time k is known, posterior PDF of target state vector can be computed as its marginal. If target present is declared, the Minimum mean-square error (MMSE) estimate of target state vector is the conditional mean of $\boldsymbol{x}_K$[13]

$$\hat{\boldsymbol{x}}_{k|k}^{MMSE} \triangleq E(\boldsymbol{x}_k|\boldsymbol{z}_k) = \int \boldsymbol{x}_k p(\boldsymbol{x}_k|\boldsymbol{z}_k) d\boldsymbol{x}_k \tag{16}$$

Consequently the estimate can be computed as

$$\hat{\boldsymbol{x}}_{k|k}^{MMSE} = \sum_{i=1}^{N_s} \boldsymbol{x}_k^{\cdot i}\cdot E_k^{\cdot i}\cdot\tilde{w}_k^i \tag{17}$$

2. Complex measurements or amplitude measurements

By comparing Eqs.(13a) and (13b) with Eqs.(14a) and (14b), it can be seen that the likelihood ratios of the amplitude measurement and the power measurement have the same form. Thus, only the situations where either the complex measurements or the amplitude measurements are used in the proposed algorithm are considered.

The resampling in the SIR filter eliminates particles that have small weights and to multiples particles with large weights. Thus particles with large weights will have more opportunities to be multiplied. Either the complex measurements or the amplitude measurements are used in the proposed algorithm will make each of the corresponding unnormalised likelihood ratio weights with a target absent equals to one, as shown in Eqs.(12b) and (13b). When a target is present the particles can be divided into two kinds, namely the desired and the undesired, according to it represented target state vector is close to or far from the true target state vector. The unnormalised likelihood ratio weights due to complex and amplitude measurements versus the SNR of the measurements are compared in Fig.1(a) and Fig.1(b), respectively. The results shown in Fig.1 are averaged over one hundred simulations. For clarity, a logarithmic (base 10) scale is used for the Y-axis in Fig.1(a).

As illustrated in Fig.1(a), both of the likelihood ratios are larger than one and growth rapidly with increasing SNR. Moreover, the likelihood ratios owing to amplitude measurements are great larger than that of complex measurements especially for moderate and large SNR values. When the particle represented state vector is far from the true one, it can be seen form Fig.1(b) that the likelihood ratios correspond to amplitude measurements are close to one under the circumstances of low and moderate SNR values and decrease rapidly with increasing SNR for high SNR values. But for the complex measurements the likelihood ratios are smaller than one and decrease with increasing SNR. However, by utilizing the amplitude measurements in the proposed algorithm, the desired particles have more opportunities to be multiplied and the undesired particles are prone to be eliminated, which results in the fast convergence of the proposed algorithm.

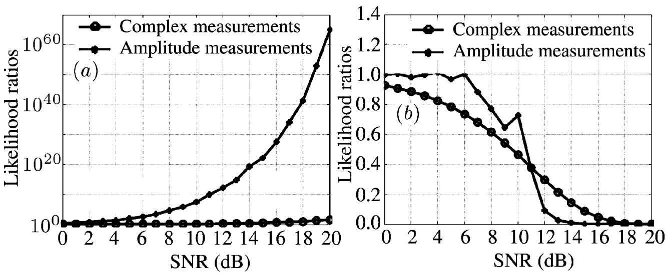


Fig. 1. Comparisons of likelihood ratios versus SNR. (a) Particle represented state vectors are close to the true state vector; (b) Particle represented state vectors are far from the true state vector

As mentioned above, improved SNR is achieved by Doppler processing. However, the phase of target echo signal introduced by target motion can seldom be completely compensated by piecewise Doppler processing as a result of limited frequency resolution. Thus a residual phase will always exist in measurements which consist of Doppler processed target echoes. However, the particle represented target Doppler frequency is located at the center of each Doppler frequency bin, the phase term of particle represented target echo signal can be completely compensated by piecewise Doppler processing. The existence of the residual phase will lead to mismatch between the real and imaginary part of the measurement and those of the particle represented signal. Without loss of generality, let the particle represented signal after Doppler processing be A, and the measurement be $Ae^{j\phi}$, where A is amplitude and φ is the residual phase. So the real and imaginary part mismatch can be computed respectively as

$$A_{real} = 2A\sin^2(\varphi/2) \tag{18a}$$

$$A_{imag} = -A\sin(\varphi) \tag{18b}$$

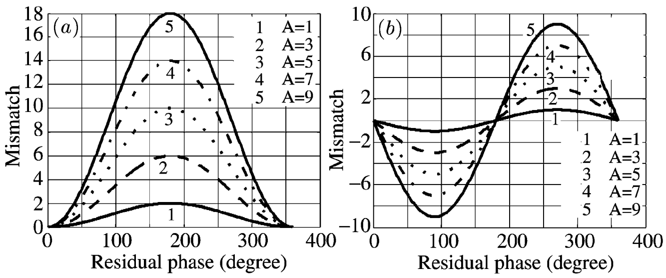


Fig. 2. Mismatches with different amplitude versus residual phase. (a) Real part mismatch; (b) Imaginary part mismatch

The mismatches with different amplitude versus residual phase are depicted in Fig.2. As illustrated in Fig.2, except for a few values of residual phase, large amplitude leads to more mismatch. Consequently, the mismatch may cause the likelihood ratios in Eq.(12a) to be far less than one especially for moderate and high SNR values. In this case the desired particles have a great probability to be eliminated result in severe performance degradation. However, the residual phase can be incorporated into target state vector to alleviate its effects at the expense of increased computational complexity.

By using amplitude measurements rather than complex measurements the proposed algorithm will converge faster and be more robust to the residual phase. In conclusion, the amplitude measurements are more suitable for the proposed algorithm.

IV. Simulations

In this section, we present an example to demonstrate the capability of the proposed particle filter based TBD algorithm for OTHR dim target detection and tracking by simulated data.

Target states are generated according to the system dynamic model given by Eq.(2). The following parameters are used in simulations, $T_k = 1$, process noise variance is $\sigma^2_{k(1)} = 0.01$ and $\sigma^2_{k(2)} = 0.001$, respectively. The background noise variance $\sigma^2_N = 25$, target echo amplitude is used to control the SNR. In each simulation the target state vector is initialised as $f^1_d = 4$ and $f^1_{da} = 0.4$. Besides, A_1 is determined by measurement SNR. The measurement SNR is defined as $10\log 10(|S_k(l)|^2/2\sigma^2_N)$. The birth and death probabilities are both set at 0.05, and $\Pr(E_1 = 1) = 0.1$, the number of particles $N_s = 6000$, the number of segments $K = 32$, a target is introduced in segment 6 and existed until segment 26, target is absent in other segments.

The estimated target existence probability by utilizing amplitude measurements and complex measurements in the proposed algorithm is illustrated in Fig.3 and Fig.4, respectively. The estimated target existence probability is calculated by Eq.(15) and averaged over one hundred simulations, for $SNR = 3$dB, 6dB, 9dB and 12dB. The target present is declared if the probability of existence is greater than 0.6, which is plotted as a horizontal line in Fig.3 and Fig.4. The asterisk signs at the bottom of the figures indicate the present of the target.

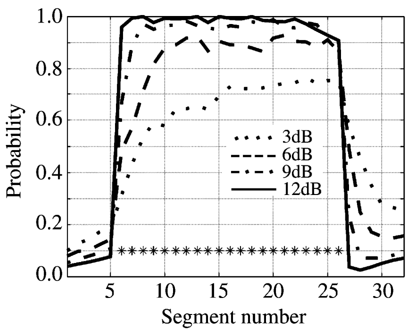


Fig. 3. Average probability of target existence by using amplitude measurements

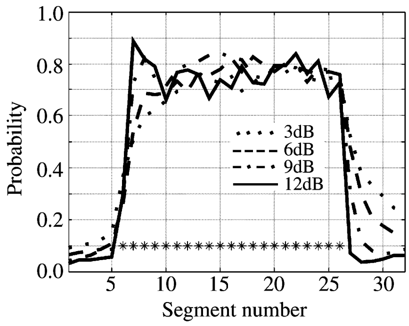


Fig. 4. Average probability of target existence by using complex measurements

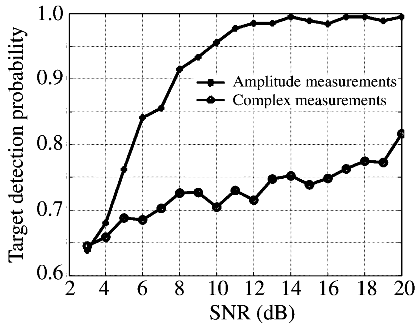


Fig. 5. Target detection probability versus SNR

It can be seen from Fig.3 that the algorithm performs very well for SNR values larger than or equal to 9dB, with no target present and absent declaration delays. For $SNR = 6$dB the detection confidence is still quite high, but there are some target present declaration delays. A few more target present declaration delays can be seen for $SNR = 3$dB than for others. Furthermore, the estimated target existence probability increases with the increase of the SNR.

It can be seen from Fig.4 that for SNR values larger than or equal to 9dB there have no target present and absent declaration delays. For $SNR = 3$dB and 6dB the target present declaration delays are smaller than that shown in Fig.3. Besides, the estimated target existence probability dos not increase with the increase of the SNR.

The estimated target detection probabilities with deferent measurements versus SNR are demonstrated in Fig.5. It can be seen from Fig.5 that both of the target detection probabilities increase with increasing SNR, but the one correspond to amplitude measurements increases more rapidly.

V. Conclusions

This paper has developed a TBD algorithm based on particle filter for OTHR dim target detection and tracking. The simulation results demonstrated that the performance of amplitude measurements is superior to that of the complex measurements. Besides, targets with a $SNR = 3$dB can be detected and tracked, although with a few target present declaration delays and lower confidence in comparison with high SNR values.

In theory the proposed algorithm may be extended to include multiple targets, but for practical implementation much work has to be done. Such as improving the algorithm efficiency by reducing the number of particles, deliberate selection of proposal density and implementing TBD algorithm based on other sequential important sampling algorithm rather than SIR, etc.

References

[1] J.M. Headrick, J.F. Thomason, "Application of high-frequency radar", *Radio Sci.*, Vol.33, No.4, pp.1045–1054, 1998.

[2] L.R. Wyatt, "Progress in the interpretation of HF sea echo: HF radar as a remote sensing tool", *IEE Proc., Radar Sonar Navig.*, Vol.137, No.2, pp.139–147, 1990.

[3] S.M. Tonissen, R.J. Evans, "Performance of dynamic programming techniques for track-before-detect", *IEEE Trans. Aerosp. Electron. Syst.*, Vol.32, No.4, pp.1440–1451, 1996.

[4] Y. Boers, J.N. Driessen, "Multitarget particle filter track before detect application", *IEE Proc., Radar Sonar Navig.*, Vol.151, No.6, pp.351–357, 2004.

[5] Y. Boers, H. Driessen, J. Torstensson *et al.*, "Track-before-detect algorithm for tracking extended targets", *IEE Proc., Radar Sonar Navig.*, Vol.153, No.4, pp.345–351, 2006.

[6] D.J. Salmond, H. Birch, "A particle filter for track-before-detect", *Proc. American Control Conf.*, Arlington, VA, pp.3755–3760, 2001.

[7] M.G. Rutten, N.J. Gordon, S. Maskell, "Recursive track-before-detect with target amplitude fluctuations", *IEE Proc., Radar Sonar Navig.*, Vol.152, No.5, pp.345–352, 2005.

[8] A. Doucet, "On sequential Monte Carlo methods for Bayesian filtering", *Tech. Rep.*, Dept.Eng., Univ. Cambridge, UK, 1998.

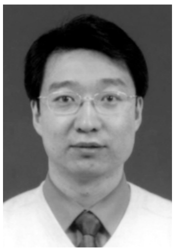
[9] M.S. Arulampalam, S. Maskell, N. Gordon *et al.*, "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking", *IEEE Trans. Signal Processing*, Vol.50, No.2, pp.174–188, 2002.

[10] N.J. Gordon, D.J. Salmond, A.F.M. Smith, "Novel approach to nonlinear/non-Gaussian Bayesian state estimation", *IEE Proc., Radar Sonar Navig.*, Vol.140, No.2, pp.107–113, 1993.

[11] J.S. Liu, R. Chen, "Sequential Monte Carlo methods for dynamical systems", *J. Amer. Statist. Assoc.*, Vol.93, No.443, pp.10321–1044. 1998.

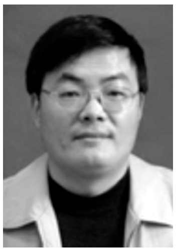
[12] A. Papoulis, S.U. Pillai, *Probability, Random Variables and Stochastic Processes*, McGraw-Hill Book Companies, London, 2002.

[13] S.M. Kay, *Fundamentals of Statistical Signal Processing*, Vol. I: Estimation theory, Prentice-Hall, Englewood Cliffs, N.J., 1993.



SU Hongtao is an associate professor in the Department of Electronic Engineering of Xidian University. His research interests include HF radar signal processing, target detection and tracking, adaptive and array signal processing, *etc.* (Email: suht@xidian.edu.cn)

SHUI Penglang is a professor in the Department of Electronic Engineering of Xidian University. He has published more than 60 journal papers, including 20 papers in international journals and eight papers in IEEE journals. His doctoral dissertation was granted the national excellent doctoral dissertation in 2002. His research interests include wavelet theory and multirate filter bank design, image processing, and radar target detection, *etc.*



LIU Hongwei is a professor in the Department of Electronic Engineering of Xidian University, he is also the director of the National Laboratory of Radar Signal Processing. His research interesting include radar automatic target recognition, wideband radar signal processing, netted radar, adaptive and array signal processing, target detection, *etc.*

BAO Zheng is a professor in the Department of Electronic Engineering of Xidian University. In 1991, he was elected as an academician of the Chinese Academy of Sciences. Currently, he is the chairman of the Academic Board of the National Key Lab of Radar Signal Processing, Xidian University, advisor of Science and Technology Committee of General Armament Department and advisor for Sci-tech Development and Cultivation of High-caliber Talents of PLA Air Force.