Detection and Tracking Low Maneuvering Target in a High Noise Environments

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***Abstract*—Detect and tracking of maneuvering target is a complicated dynamic state estimation problem whose difficulty is increased in case of high noise environments or low signal-to-noise ratio (SNR). In this case, the track-before-detect filter (TBDF) that uses unthresholded measurements considers as an effective method for detecting and tracking a single target under low SNR conditions. Nevertheless, the performance of the algorithm will be affected with severe loss because of the mismatching of target model during maneuver. In this paper, to resolve the target maneuvers, we propose an application of particle filtering which depends on track before detect (PF-TBD) algorithm in order to track the maneuvering target. We employ the Constant Acceleration (CA) model and Coordinate Turn model (CT). Our simulation results show that the detection and tracking of maneuvering target performance of TBD-PF has been improved using the proposed algorithm.**

Keywords—target tracking; track before detect; particle filter; detection

I. Introduction

Radar tracking systems advancement for defense purpose is began as early as 1930 and came to be an active for study topic with the progress of the Kalman's filter (KF) in 1960 [1]. The research is initially concentrated on tracking the target in the defense application for air and maritime and for guidance radar systems. With the generation and development of new advancement in computational processing and capabilities of embedded processing, the technology of radar penetrating is increased to be in lots of fields such as air-traffic control in aim of commercial air travel, radar of weather surveillance used for locating precipitation [2], radar system of vehicle collision avoidance [3], talker tracking in speech processing [4], image processing [5], robotics [6], applications of remote sensing [7], and biomedical applications [8]. All of these kinds of different applications are to enhance the robustness of target tracking algorithms bases on different issues.

The traditional method of target tracking is built upon target measurements (position, range rate, acceleration and others), which are evolved through thresholding the outcome of a signal processing unit from a sensor of monitoring [9]. The main purpose of thresholding is to minimize the data flow and then make the tracking easy. Moreover, conserving of a target produced from signal-to-noise ratio (SNR), the selection of the recognition threshold is basically depending on the probability of target recognition and the quantity of false alarms. Thus, the rate of false alarm, alternatively, has an effect on the complexity of the data organization issue in the tracking system. As a whole, higher densities of false alarms need to more advanced data association algorithms.

The undesirable influence of thresholding the sensor data, is definitely limiting the data flow, it contributes to get rid of extremely useful information. On the other hand, in high SNR targets which loss of information, it is slightly a problem because one can accomplish good probability recognition of the target with a small rate of false alarm. Recently, the developments of stealthy military aircraft and cruise missile have highlighted the requirement of detecting and tracking the target with low SNR. Therefore, for these kinds of stealthy targets, there is a significant benefit in using the unthresholded data for synchronized recognition and track innovation [10] [11]. Relying on the kinds of used sensor, the unthresholded data can possibly be a sequence of range-Doppler maps (for radar), bearing-frequency distributions (applied in case of passive sonar).

The principle of synchronized recognition and tracking by utilizing unthresholded data is recognized very well in academic research works as the approach of track-before-detect (TBD). Usually, TBD is employed as a set of algorithms making use of the Hough transform [12], dynamic programming [10] [11], or the algorithm of maximum likelihood estimation [13].

TBD algorithms based upon the Hough transformation, dynamic programming or maximum likelihood methods are typically computationally extensive [14]. Thus, using recent advancement in Sequential Monte Carlo methods, TBD algorithms applied by particle filter (PF) are making possible the computation [15] [16]. Particle filters consider an effective solution using in the nonlinear filtering problem as they can. Theoretically, it can approximate any posterior density without any hypothesis concerning the linearity of the process or observation model or the Gaussian nature of process and observation noise. Furthermore, particle filters remain tractable in case of increasing the state dimension. The state vector may involve different target parameters as position, velocity, acceleration, Intensity and the variable of detection. Thus, in our examples, these parameters produce a state vector with dimensions seven for CA model and five for CT model [17].

The performance of PF-TBD algorithm will be hardly suffering severe from losing accuse of mismatching of target when maneuver is occurred, which led to heavily restriction of application by the model with many realistic scenarios [18]. Therefore, the maneuvering trajectory can be defined in many options, representing by constant acceleration model, coordinated turn motion and constant jerk model [18] [19] .

In this paper, we apply PF-TBD algorithm for maneuvering target using the constant acceleration and coordinate turn model [18]; moreover, our formulation and application are mainly depending on the principles of particle filter [15], [20]. The PF is dependent to TBD and integrates unthresholed data and a binary target existence variable into the target state estimation process. The target existence and absence are clearly modelled [21] [22]. Thus, this principle allows us to determine the probability of target existence directly from the filter.

The remaining of this paper is organized as the follows: section 2 presents the dynamic system by considering two typical target tracking examples in which the motion of a target is estimated using 2-D constant acceleration and coordinate turn model. In section 3, the measurement model is introduced for the TBD application. While section 4 presents the formulation of the TBD approach as a nonlinear filtering problem and describes the theoretical recursive Bayesian solution. The implementation of the solution using a particle filter is presented in section 4. Then, section 5 gathers our simulations and results. Finally, the paper ends with the conclusions and the perspectives for future research in section 6.

II. PROBLEM FORMULATION

A. Maneuvering Target Models

We assume that we want to track a maneuvering target moving in a 2-D plane with an unknown state vector s_k at time step k. We consider the state model given by:

$$s_{k+1} = Fs_k + v_k \tag{1}$$

Where F is the process of transition matrix, v_k is a process of Gaussian noise with zero mean and covariance Q. k is the discrete-time index and s_k is the state vector defined in the coming motion models:

1) Constant Acceleration Model (CA)

Supposing that the motion consists of Wiener-Process Acceleration model [19]. It is also indicating to simply as the constant acceleration (CA) model, which could be defined by (1). Where $s_k = [x_k \quad \dot{x}_k \quad \ddot{x}_k \quad y_k \quad \dot{y}_k \quad \ddot{y}_k \quad I_k]^T$ consists of position (x_k, y_k), velocity $(\dot{x}_k, \dot{y}_k)$, maneuvring acceleration $(\ddot{x}_k, \ddot{y}_k)$ in the plane, and the intensity I_k. The transition matrix F_{CA} and the noise process covariance Q_{CA} are given by:

$$F_{CA} = \begin{bmatrix} 1 & T & T^2/2 & 0 & 0 & 0 & 0 \\ 0 & 1 & T & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & T^2/2 & 0 \\ 0 & 0 & 0 & 0 & 1 & T & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$Q_{CA} = \begin{bmatrix} \frac{q_1T^5}{20} & \frac{q_1T^4}{8} & \frac{q_1T^3}{6} & 0 & 0 & 0 & 0 \\ \frac{q_1T^4}{8} & \frac{q_1T^3}{3} & \frac{q_1T^2}{2} & 0 & 0 & 0 & 0 \\ \frac{q_1T^3}{6} & \frac{q_1T^2}{2} & T & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{q_1T^5}{20} & \frac{q_1T^4}{8} & \frac{q_1T^3}{6} & 0 \\ 0 & 0 & 0 & \frac{q_1T^4}{8} & \frac{q_1T^3}{3} & \frac{q_1T^2}{2} & 0 \\ 0 & 0 & 0 & \frac{q_1T^3}{6} & \frac{q_1T^2}{2} & T & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & q_2T \end{bmatrix} \tag{2}$$

Where T is the sampling period and q_1, q_2 denote the level of process noise in target motion and intensity, respectively.

2) Coordinate Turn Model (CT)

Consider the target moves with coordinate turn model. Where $s_k = [x_k \quad \dot{x}_k \quad y_k \quad \dot{y}_k \quad I_k]^T$, in the Cartesian coordinates. Equation (1) gives its discrete-time equivalent. Where the transition matrix F_{CT} and the noise process covariance Q_{CT} are given by:

$$F_{CT} = \begin{bmatrix} 1 & \frac{sin\Omega T}{\Omega} & 0 & -\frac{(1-cos\Omega T)}{\Omega} & 0 \\ 0 & \cos\Omega T & 0 & -\sin\Omega T & 0 \\ 0 & \frac{(1-\cos\Omega T)}{\Omega} & 1 & \frac{\sin\Omega T}{\Omega} & 0 \\ 0 & \sin\Omega T & 0 & \cos\Omega T & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$Q_{CT} = \begin{bmatrix} \frac{2q_1(\Omega T - sin\Omega T)}{\Omega^3} & \frac{q_1(1-cos\Omega T)}{\Omega^2} & 0 & \frac{q_1(\Omega T - sin\Omega T)}{\Omega^2} & 0 \\ \frac{q_1(1-cos\Omega T)}{\Omega^2} & q_1T & -\frac{q_1(\Omega T - sin\Omega T)}{\Omega^2} & 0 & 0 \\ 0 & -\frac{q_1(\Omega T - sin\Omega T)}{\Omega^2} & \frac{2q_1(\Omega T - sin\Omega T)}{\Omega^3} & \frac{q_1(1-cos\Omega T)}{\Omega^2} & 0 \\ \frac{q_1(\Omega T - sin\Omega T)}{\Omega^2} & 0 & \frac{q_1(1-cos\Omega T)}{\Omega^2} & q_1T & 0 \\ 0 & 0 & 0 & 0 & q_2T \end{bmatrix} \tag{3}$$

Where Ω is nearly constant angular turn rate, T is the sampling period. q_1 and q_2 denote the level of process noise in target motion and intensity, respectively.

B. Transition matrix

A target can possibly be present or absent from the surveillance region at time step k. Target existence variable m_k is modelled by a two-state Markov chain, that is $m_k = \{0,1\}$. Where the number 0 denotes the event that a target is not present, while the number 1 denote the contrary. However, we assume that transitional probabilities of target birth P_b and death P_d are known, defined as:

$$P_b \triangleq P\{m_k = 1 | m_{k-1} = 0\} \tag{4}$$

$$P_d \triangleq P\{m_k = 0 | m_{k-1} = 1\} \tag{5}$$

The probability of staying alive and the probability of remaining absent are given by:

$$1 - P_b \triangleq P\{m_k = 0 | m_{k-1} = 0\} \tag{6}$$

$$1 - P_d \triangleq P\{m_k = 1 | m_{k-1} = 1\} \quad (7)$$

Thus, the transitional probability matrix (TPM) is given by:

$$\Gamma = \begin{bmatrix} 1 - P_b & P_b \\ P_d & 1 - P_d \end{bmatrix} \quad (8)$$

C. Measurement Model

The sensor supplies a series of two-dimensional images (frames) of the monitoring area; every image is composed of $(N_x \times N_y)$ representing the resolution cells. A resolution cell relates a rectangular area of dimensions $\Delta_x \times \Delta_y$ in order that the center of every cell (i, j) is determined to be at $(i\Delta_x \times j\Delta_y)$ for $i = 1, \ldots., N_x$ and $j = 1, \ldots. N_y$.

Monitored images will be recorded at discrete instant k with the sampling interval T. At every resolution cell (i, j) the computed intensity is signified as $z_k^{(i,j)}$ and modelled as:

$$z_k^{(i,j)} = \begin{cases} \Psi_k^{(i,j)}(s_k) + \omega_k^{(i,j)} & if \;\; m_k = 1 \\ \omega_k^{(i,j)} & if \;\; m_k = 0 \end{cases} \quad (9)$$

Where $\Psi_k^{(i,j)}(s_k)$ refers to the contribution of target to intensity level in the resolution cell (i, j) while $\omega_k^{(i,j)}$ representing the measurement noise in the resolution cell (i, j), assumed to become independent from pixel to pixel and also from frame to frame.

In the other hand, for a point target which has the intensity I_k at position (x_k, y_k), the contribution to pixel (i, j) is approximated expressed in approximation way as:

$$\Psi_k^{(i,j)}(s_k) \approx \frac{\Delta_x \Delta_y I_k}{2\pi\Sigma^2} \exp\left\{-\frac{(i\Delta_x - x_k)^2 + (j\Delta_y - y_k)^2}{2\Sigma^2}\right\} \quad (10)$$

Where Σ is defined as the volume of blurring exposed by the sensor.

The finished measurements are recorded at time k a $n \times m$ matrix given as:

$$\mathrm{z}_k = \left\{z_k^{(i,j)} : i = 1, \ldots, n, j = 1, \ldots, m\right\} \quad (11)$$

While the set of final measurements gathered as much as time k which signified customarily as:

$$\mathrm{Z}_k = \{z_i, i = 1, \ldots k\} \quad (12)$$

III. Bayesian Estimator

TBD problem is formulated in the framework of recursive Bayesian estimation as follows: Given the joint posterior pdf of target state and target existence $p(s_{k-1}, m_{k-1} | Z_{k-1})$ at time $k-1$, and given the recent available frame z_k, the aim is to construct the joint posterior pdf $p(s_k, m_k | Z_k)$ at time k. The formal recursive Bayesian solution can be presneted as a two-step procedure, consisting of prediction and update [14] [23].

A. Prediction

If the target is absent in the data ($m_k = 0$), the target state is not defined. Assuming the target is present in the data ($m_k = 1$), the prediction step can be expressed as:

$$p(s_k, m_k = 1 | Z_{k-1}) = (1 - P_d) \int p(s_k | s_{k-1}, m_k = 1, m_{k-1} = 1) p(s_{k-1}, m_{k-1} | Z_{k-1}) ds_{k-1} + p_b(s_k) P_b \quad (13)$$

The pdf $p_b(s_k)$ denotes the initial target density on its appearance.

B. Update

The update equation is given by:

$$p(s_k, m_k = 1 | Z_k) = \frac{p(z_k | s_k, m_k = 1)\, p(s_k, m_k = 1 | Z_{k-1})}{p(z_k | Z_{k-1})} \propto l(z_k | s_k, m_k = 1) p \quad (14)$$

Where $p(s_k, m_k = 1 | Z_{k-1})$, and $p(z_k | x_k, m_k)$ are the prediction density and the likelihood function given by (13), and (15) respectively.

C. Likelihood Function

The likelihood functions can be presented as:

$$p(z_k | s_k, m_k) = \begin{cases} \prod_{i=1}^{n} \prod_{j=1}^{m} p\left(z_k^{(i,j)} \middle| s_k, m_k = 1\right), & for \;\; m_k = 1 \\ \prod_{i=1}^{n} \prod_{j=1}^{m} p\left(z_k^{(i,j)} \middle| m_k = 0\right), & for \;\; m_k = 0 \end{cases} \quad (15)$$

Here $p\left(z_k^{(i,j)} \middle| m_k = 0\right)$ is defined as the pdf of background noise in pixel (i, j), awhile $p\left(z_k^{(i,j)} \middle| s_k, m_k = 1\right)$ is the likelihood of target signal plus noise in pixel (i, j), given that the target in state s_k. Thus, supposing the measurement noise is Gaussian, which is independent of pixel-to-pixel, both of probability density functions can be then given as expressed as:

$$p\left(z_k^{(i,j)} \middle| s_k, m_k = 1\right) = \mathcal{N}\left(z_k^{(i,j)}; \Psi_k^{(i,j)}(s_k), \sigma^2\right) \quad (16)$$

$$p\left(z_k^{(i,j)} \middle| m_k = 0\right) = \mathcal{N}\left(z_k^{(i,j)}; 0, \sigma^2\right) \quad (17)$$

Since the target will have an effect only on the pixels in the vicinity of its location $(x_k y_k)$, the statement for $p(z_k | s_k, m_k = 1)$ can be possibly be approximated as follows:

$$p(z_k | s_k, m_k = 1) \approx \prod_{i \in \alpha_i(s_k)} \prod_{j \in \alpha_j(s_k)} p\left(z_k^{(i,j)} \middle| s_k, m_k = 1\right) \cdot \prod_{i \notin \alpha_i(s_k)} \prod_{j \notin \alpha_j(s_k)} p\left(z_k^{(i,j)} \middle| m_k = 0\right) \quad (18)$$

Where $\alpha_i(s_k)$ and $\alpha_j(s_k)$ are the sets of subscripts i and j, respectively, corresponding to pixels impacted by the target.

Thus, for our application, we need to introduce the likelihood ratio in pixel (i, j) for a target in state s_k^n, which given by:

$$L\left(z_k^{(i,j)}\middle|s_k^n, m_k\right) = \begin{cases} \dfrac{p\left(z_k^{(i,j)}\middle|s_k^n, m_k = 1\right)}{p\left(z_k^{(i,j)}\middle|m_k = 0\right)} & m_k = 1 \\ 1 & m_k = 0 \end{cases} \quad (19)$$

We replace by the probability density function of $p\left(z_k^{(i,j)}\middle|s_k, m_k = 1\right)$ and $p\left(z_k^{(i,j)}\middle|m_k = 0\right)$, we found:

$$L\left(z_k^{(i,j)}\middle|s_k, m_k\right) = \begin{cases} \exp\left\{-\dfrac{\Psi_k^{(i,j)}(s_k)\left(\Psi_k^{(i,j)}(s_k)-2z_k^{(i,j)}\right)}{2\sigma^2}\right\} & m_k = 1 \\ 1 & m_k = 0 \end{cases} \quad (20)$$

Where $\Psi_k^{(i,j)}$ was actually described in (10). Equation (20) follows from (16), (17), and (19). The likelihood ratio can be expressed as:

$$L\left(z_k^{(i,j)}\middle|s_k, m_k\right) = \begin{cases} \prod_{i\in C_i(s_k^n)}\prod_{j\in C_j(s_k^n)} \exp\left\{-\dfrac{\Psi_k^{(i,j)}(s_k)\left(\Psi_k^{(i,j)}(s_k)-2z_k^{(i,j)}\right)}{2\sigma^2}\right\} & m_k = 1 \\ 1 & m_k = 0 \end{cases} \quad (21)$$

IV. A PARTICLE FILTER IMPLEMENTATION OF TRACK-BEFORE-DETECT

The algorithm of a single cycle of the current particle filter, indicated in this work by TBD Particle filter for manoeuvring target, which is defined in the following steps:

Step1: particle set $\{(s_{k-1}^n, m_{k-1}^i), \omega_{k-1}^i\}_{i=1}^N$ at step $k-1$.

Step2: Draw m_k according to the transition matrix defined in (8).

Step3: The prediction of particle target states, only for particles defined by $m_k^n = 1$. There are two possible cases here:

a) Newborn particles ($m_{k-1}^n = 0$, $m_k^n = 1$): particles of the target state are uniformly drawn by the proposal density $s_k^n \sim q_b(s_k|m_k^n = 1, m_{k-1}^n = 0, z_k)$ at time step k.

b) Existing particles ($m_{k-1}^n = 1$, $m_k^n = 1$): this is a group of particles that continues to stay "alive", The target dynamic model in equation (1) can be used to update the target state particles. We need to compute the importance weights $\widetilde{\omega}_k^n$ using the likelihood ratio as [15]:

$$\widetilde{\omega}_k^n = \begin{cases} \prod_{i\in\alpha_i(s_k^n)}\prod_{j\in\alpha_j(s_k^n)} L\left(z_k^{(i,j)}\middle|s_k^n\right) & if \quad m_k^n = 1 \\ 1 & if \quad m_k^n = 0 \end{cases} \quad (22)$$

Step4: Calculate the normalize weights $\omega_k^n = \frac{\widetilde{\omega}_k^n}{\sum_{n=1}^N \widetilde{\omega}_k^n}$

Step5: Compute the effective sample size $N_{eff} = \frac{1}{\sum_{n=1}^N (\omega_k^n)^2}$

Step6: Make a test of degeneracy problem $N_{eff} < N_{th}$

Step7: Resampling$\left[\left\{s_k^n, \frac{1}{N}\right\}_{n=1}^N\right] = resampling[\{s_k'^n, w_k'^n\}_{n=1}^N]$

Step8: Output PF-TBD: The PF-TBD perform target detection using the estimation of the posterior probability of target existence at time k. This estimation is computed as:

$$\hat{P}_k = \frac{\sum_{n=1}^N m_k^n}{N} \quad (23)$$

With satisfaction range $0 < \hat{P}_k < 1$. This declaration can then trigger the initialization of a track depending on the estimated target state

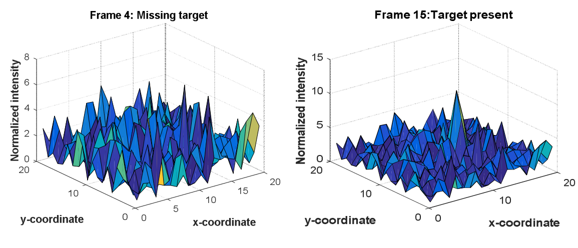
$$\hat{s}_{k/k} = \frac{\sum_{n=1}^N s_k^n \cdot m_k^n}{\sum_{n=1}^N m_k^n} \quad (24)$$

V. SIMULATION AND RESULTS

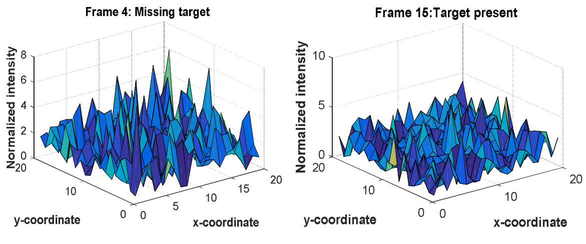
We consider two scenarios of a maneuvering target tracking example (CA, CT). A sequence of 30 frames of data has been generated with the following parameters: Each frame consists of an array of $(N_x \times N_y)$ pixels, where $N_x = N_y = 20$; each cell has a pixel resolution $\Delta_x = \Delta_y = 1$, Background noise level in each pixel is $\sigma = 2$, and the blurring parameter $\Sigma = 0.7$. The target is absent from frame 1 to frame 5 and is present from frames 6 to 25 before disappearing from frames 26 to 30.The initial states are $[4.2 \;\; 0.45 \;\; 0.1 \;\; 7.2 \;\; 0.25 \;\; 0.1 \;\; I_0]^T$, $[4.2 \;\; 0.45 \;\; 7.2 \;\; 0.25 \;\; I_0]^T$ for CA and CT models respectively. The level of process noise used in the target movement model is $q_1 = 0.001$ and $q_2 = 0.01$. The simulations are conducted under an initial intensity $I_0 = 10{,}13{,}25$, which relates to an SNR=4.21,6.49,12.17 dB, respectively, $\Omega = 6°/s$ is a constant angular rate for CT model. The particle filter parameters are selected as follows: $P_b = P_d = 0.05$; initial probability of existence $p_0 = 0.05$; $threshold = 2$. The initial value of particles proposal functions as detailed in [24], with the positions, velocities, acceleration and target intensities given by $x_k^b \sim U(0, n\Delta_x)$, $y_k^b \sim U(0, m\Delta_y)$, $\dot{x}_k^b \sim U(-1,1)$, $\dot{y}_k^b \sim U(-1,1)$, $\ddot{x}_k^b \sim (-0.5, 0.5)$, $\ddot{y}_k^b \sim (-0.5, 0.5)$, $I_k^b \sim (I_0 - 5, I_0 + 5)$, respectively. The number $p = 2$ is the number of vicinity pixels used to compute the likelihood function, where the number of particles N=20000. The simulation results are evaluated on an average over 50 Monte Carlo runs using an Intel Xeon workstation (3.47GHz CPU, 24.0 Go RAM).

A. Scenario 1 (CA model)

Figure (1) indicates frame 4 and 15 of data sequence measurements at 6.49 and 12.17dB peak SNR.



(a)



(b)

Fig. 1. Measurements Frames (4, 15): (a) for 12.17 dB Peak SNR. (b) for 6.49 dB Peak SNR.

In figure (1-a), for high a SNR (SNR=12.17 dB), we can easily detect the target using a classical method. In figure (1-b), it is very difficult to detect the target by classical method at this low value of SNR (SNR=6.49dB).

Figure (2) to Figure (4) present The PF-TBD outputs. Figure (2) shows the detection performance given by the estimation of the existence probability at 12.17, 6.49 and 4.21dB peak SNR.

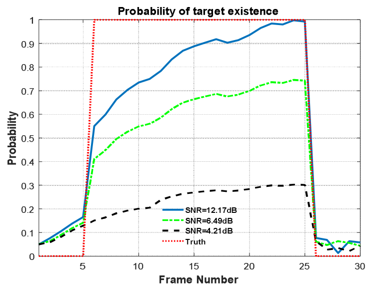


Fig. 2. Probability of target existence for PF-TBD filter using CA model

The PF-TBD needs only some frames, after enters of the target in the surveillance region to establish that the target is existing. Then, the existence probability is still increase above frame 7 until frame 20 and still stable until frame 25. Therefore, it drops sharply in frame 25 when the target disappears from the surveillance region.

Figure (3) displays the true and the estimated target trajectory produced by the PF-TBD filter. From this figure (3), the estimate and the true trajectory are very close.

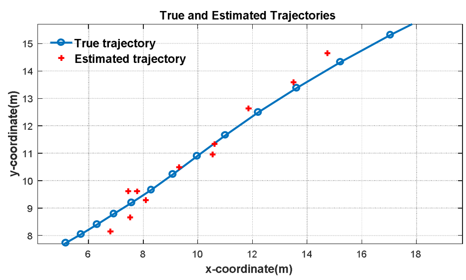


Fig. 3. True and estimated trajectory of maneuvering target using CA model at 6.49 dB Peak SNR

Figure (4) show the result of estimate RMSE in position at different SNR values for PF-TBDF algorithm.

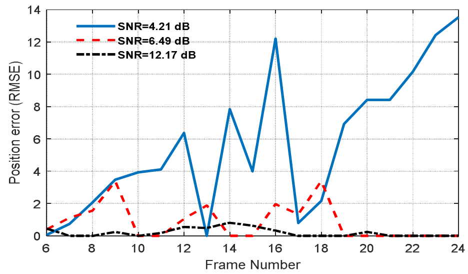


Fig. 4. Position RMSE for the PF-TBD filter using CA model at 12.17 and 6.49 dB Peak SNR

It is can be seen that the algorithm has a lower RMSE when the target began to appear in SNR=12.17dB. However, when the SNR reduce the RMSE decrease after three frames from target appear. Consequently, the PF-TBDF is capable of tracking the maneuvering target using with low SNR CA model.

B. Scenario 2 (CT model)

Similarly, to the first scenario Figure (5), it indicates two frames of data sequence measurements.

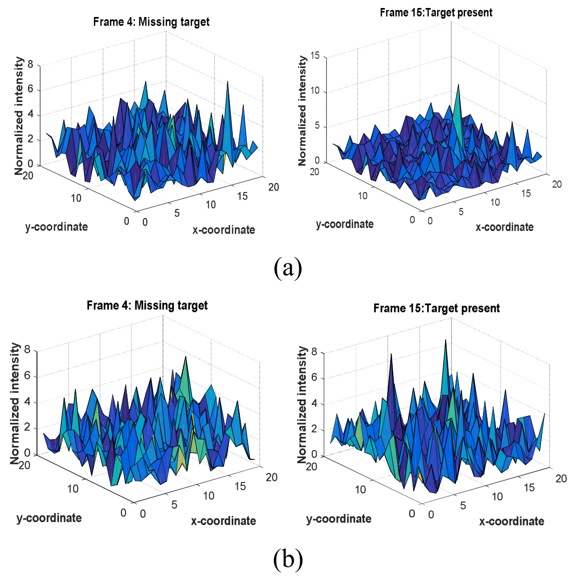


Fig. 5. Measurements Frames (4, 15) : (a) for 12.17 dB Peak SNR. (b) for 6.49 dB Peak SNR

Figure (6) shows the estimation of the existence probability for CT model.

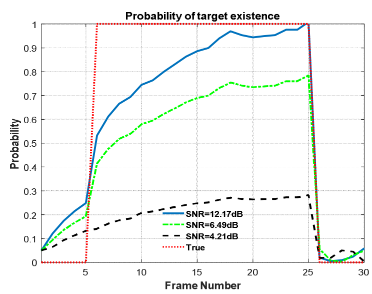


Fig. 6. Probability of target existence PF-TBD filter using CT model.

It should be mentioned that, the existence probability still stable above 16 until frame 25. Therefore it drops sharply as shown in frame 26, in case of the target is not present anymore.

Figure (7) displays true and estimated target positions against the track, produced by PF-TBD filter. Note how the target trajectory deviates slightly from the curve line due to process noise.

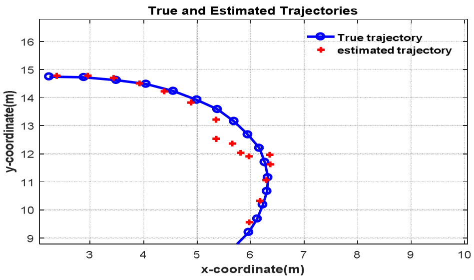


Fig. 7. True and estimated target trajectory of maneuvering target using CT model at 6.49dB.

Figure (8) shows the estimate Root Mean Square Error in position at different SNR values for PF-TBDF algorithm.

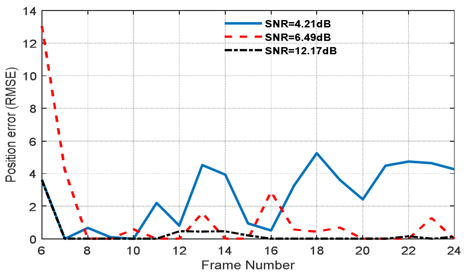


Fig. 8. Position RMSE for the PF-TBD filter using CT model at 12.17, 6.49 and 4.21dB Peak SNR.

It is can be seen that the algorithm has a lower RMSE when the target began to appear in SNR=12.17dB but when the SNR is reduced the RMSE decreases after three frames from target appear. Therefore, the PF-TBDF is capable of tracking the maneuvering target using low SNR CT model.

VI. CONCLUSION

In this paper, to manipulate low maneuvering weak targets, the PF-TBD algorithm is proposed for two dynamics models (CA and CT). The major advantage of the track-before-detect approach based on target existence variable and as a result, the developed particle filter can detect and track low SNR maneuvering target. The results from the simulation show that the PF-TBD algorithm has a successfully detection and tracking performance, both for constant acceleration and coordinate turn models of maneuvering targets, under severe conditions such as high noise or low SNR. Therefore, further work will mainly concentrate on how to detect and track maneuvering weak targets with multiple.

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