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Infrared Dim Target Detection and Tracking Based on Particle Filter

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Abstract: Since the distance attenuation and the strong noise, Infrared Radiation (IR) dim target detection and tracking is challenging in recent years. Under this circumstance, conventional particle filter track-before-detect (PF-TBD) algorithm cannot detect and track effectively. In this paper, a feasible two-layer particle filter based algorithm is proposed for this problem. The proposed algorithm can overcome the shortcomings of conventional particle filter (PF) algorithm. By introducing local particle swarm reset method and particle swarm optimization (PSO) algorithm, it is suitable for low-observable multi-target detection and tracking, and has a good performance of infrared dim target detection and tracking in simulations.

Key Words: Low-Observable, Multi-Target, Dim Target, Particle Filter

1 Introduction

Passive infrared detection technology is an important technology for the detection and tracking of air targets in recent years. It can make up for the drawback of radar systems because of its advantages such as good concealment and high resolution [1, 2]. However, Infrared Radiation (IR) dim target detection and tracking is challenging because of the distance attenuation and the strong noise. The Signal Noise Ratio (SNR) of Infrared signal is always low. The conventional tracking algorithm is difficult to detect and track the IR dim target effectively. To overcome this problem, effective algorithms for tracking low- observable target need to be proposed.

In general, the challenges of low-observable target detection and tracking can be summarized as the following three aspects. First, the number of tracking targets in the surveillance area is always unknown and time-varying. Despite a lot of methods have been proposed to solve multi-target tracking problem [3, 4], they always need to confirm the number of targets. Second, the Signal Noise Ratio of the low-observable target signal is very low, usually below 10dB. It is hard to detect and track those targets because of the interference of the noise. Third, the size of target is very small, with few pixels in the infrared image. Because of the lack of shape and structure information, small target cannot be detected and tracked by the pattern recognition method of the target shape feature. In the field of IR dim target detection and tracking, how to solve these problems is the core issue.

In recent years, with the improvement of related theory, the track-before-detect (TBD) technique has been developed rapidly, and it has been widely used as a new idea in the field of target detection and tracking. The TBD technique is an effective method for low-observable target detection and tracking. It improves the detection performance of the low-observable target through the multi-frame data accumulation [5]. In this case, many methods based the TBD technique have been proposed to solve the problem of low-observable target detection and tracking. Among of them, the particle filter (PF) method has gotten much attention in the target tracking filed. Since particle filter is suitable for non-linear and non-Gaussian environment, it is always used for target tracking with infrared image observation model. In 2001, Salmond proposed a particle filter track-before-detect (PF-TBD) algorithm based on Bayesian framework [6]. This algorithm is easier to achieve in engineering because of the low requirement of calculation and storage. Subsequently, some researches have proposed the method to use the weight of particle to calculate the probability of the target's existence [7].

However, there are still a lot of limitations of conventional PF-TBD algorithm for low- observable target detection and tracking. First, conventional PF-TBD algorithm is only for tracking a single target. In order to track the unknown and time-varying number of targets, Ref.[8] proposed an effective method to assign each target a particle filter for tracking. And another particle filter was applied in the surveillance area for detecting new target. This method can transform the multi-target tracking problem into multiple single-target tracking problems. Its drawback is that it can only detect the appearance of a single target. Second, when the particle filter is used for target tracking, the lack of diversity among the particles can cause the problem of particle collapse, which means most particles will collapse into a small area by the resampling procedure. Although some methods were presented in [9] to improve the diversity among the particles, these methods are not suitable for multi-target tracking. If a particle filter is applied in the surveillance area for multi-target detection and tracking, most particles are possibly concentrated round one target, and it is difficult to estimate the states of other targets effectively [10]. Third, conventional PF-TBD algorithm is not suitable for small target tracking because of the problem of particle impoverishment. The probability of particles falling on the target is relatively low, which makes the sampling efficiency very low [11, 12]. And after several iterations, the particles can hardly converge to the real state. To overcome this problem, conventional particle filter

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methods require a large number of particles in order to ensure the accuracy of estimation. Some intelligent algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were proposed to overcome the problem of particle impoverishment [13-15].

In this paper, a feasible two-layer particle filter based algorithm is proposed for Infrared Radiation dim target detection and tracking. This algorithm can deal with the problem of tracking an unknown, time-varying number of targets. Besides, some methods are presented to overcome the drawbacks of conventional PF-TBD algorithm for low-observable target detection and tracking. On one hand, a new method based on particle swarm reset is proposed for particle collapsing problem. On the other hand, by introducing particle swarm optimization algorithm into the conventional particle filter. This algorithm works well to overcome the problem of particle impoverishment for small target tracking.

2 Multi-target Tracking Problem Formulation

In this section, we will consider a multi-target tracking problem formulation based on infrared sensor. Multi-target motion model and infrared image observation model will be described in the following.

2.1 Target Motion Model

In the research of target tracking, the constant velocity model is widely adopted. It is assumed that multiple targets move with constant velocity in the X-Y plane, and the movement of each target is independent of each other. The state of the single target can be decomposed as $s_k = \begin{bmatrix} x_k & y_k & \dot{x}_k & \dot{y}_k \end{bmatrix}^{\mathrm{T}}$, where x_k and y_k represent the target's position coordinates at the time k, $\dot{x}_k$ and $\dot{y}_k$ represent the target's velocity at the time k. A recurrence equation of the discrete-time constant velocity model is as follows

$$s_k = Fs_{k-1} + w_{k-1} \tag{1}$$

where F is the state transition matrix, defined as follows

$$F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where T represents the sampling period. $w_{k-1} \sim N(0, Q)$, where the process noise covariance matrix is given by

$$Q = \begin{bmatrix} \alpha T^3/3 & \alpha T^2/2 & 0 & 0 \\ \alpha T^2/2 & \alpha T & 0 & 0 \\ 0 & 0 & \alpha T^3/3 & \alpha T^2/2 \\ 0 & 0 & \alpha T^2/2 & \alpha T \end{bmatrix} \tag{3}$$

where α is the state process noise intensity.

In addition, since the target does not always exist in the multi-target tracking problem. It is possible to appear and disappear at any time. We need to model the existence state of the target. It is assumed that the appearance and disappearance processes of each target are independent of each other. E_k is used to represent the existence state of a single target at the time k, where E_k=0 indicates that the target does not exist, and E_k=1 indicates that the target is existing. The Markov transformation probability matrix of the target's existence state is

$$P = \begin{bmatrix} 1 - P_b & P_b \\ P_d & 1 - P_d \end{bmatrix} \tag{4}$$

where P_b and P_d represent the probability of target's birth and death, which can be obtained as

$$P_b = p\left(E_k = 1 \mid E_{k-1} = 0\right) \tag{5}$$

$$P_d = p\left(E_k = 0 \mid E_{k-1} = 1\right) \tag{6}$$

2.2 Measurement Model Based on Infrared Sensor

In this paper, the infrared image observation model is adopted in simulation as a measurement model. Since the problem of the low-observable target detection and tracking mainly involves the dim target which is smaller than the sensor resolution. The observation model generally adopts the form of point spread model. We reference the method in [16] to establish the infrared observation model. It is assumed that the original data of measurement in a frame is received from $n_x \times m_y$ resolution units. The size of each resolution unit is $\Delta_x \times \Delta_y$. Consequently, the observation data of the sensor can also be represented by a 2-D gray image in the surveillance area. The observation taken by infrared sensor in resolution unit (m, n) at the time k is modeled as follows

$$z_k^{(m,n)} = \begin{cases} \sum_{t=1}^{N_T} h_k^{(m,n)} + v_k^{(m,n)}; & \text{targets exist} \\ v_k^{(m,n)}; & \text{no target} \end{cases} \tag{7}$$

Where $h_k^{(m,n)}$ is the signal of the tth target in the resolution unit (m, n) at time k, and $v_k^{(m,n)}$ is the observation noise of the sensor in resolution unit (m, n) which is assumed to be zero mean Gaussian with the variance σ^2. N_T represents the number of tracking targets in the surveillance area. It is assumed that the noise from each resolution unit or each frame signal is independent of each other. Due to the blurring of the infrared sensor, it has an influence on the neighboring resolution units. And the strength of signal in the resolution unit adopts the sensor point spread function. The strength of signal from the point target located at (x_k, y_k) in resolution unit (m, n) can be approximated as

$$h_k^{(m,n)}(s_k) = \frac{\Delta_x \Delta_y I_k}{2\pi\Sigma^2} \times \exp\left(-\frac{(x_k - m\Delta_x)^2 + (y_k - n\Delta_y)^2}{2\Sigma^2}\right) \tag{8}$$

Where Σ represents the sensor fuzzy coefficient, and I_k is the amplitude parameter of the target's signal.

The signal noise ratio of the target h_k can be calculated as follows

$$\mathrm{SNR} = 10\log\frac{\max_{m,n}\left(\left|h_k^{(m,n)}\right|^2\right)}{2\sigma^2} \tag{9}$$

Infrared observation simulation for the target signal modeling generally adopts the sensor point spread function, and the practical application of this approach can prove its effectiveness.