

Pedestrian Target Tracking Method in Low SNR Ratio Scenarios

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ABSTRACT

Millimeter-wave radar is widely used in intelligent transportation and autonomous driving. However, due to the lack of coordination among radar systems, it is susceptible to interference from signals emitted by other radar systems, leading to issues such as increased background noise. To address this problem, this paper proposes a pedestrian target tracking method for low signal-to-noise ratio (SNR) scenarios. By leveraging the particle filtering method and simulating a large number of particles to approximate probability distributions, this method effectively resolves target tracking issues caused by increased background noise. Experimental results demonstrate that the proposed algorithm exhibits excellent tracking performance in low SNR radar scenarios.

KEYWORDS

Autonomous Driving; Radar System; Pedestrian Target Tracking; Increased Background Noise.

1. INTRODUCTION

With the rapid development of intelligent transportation systems and autonomous driving technologies, millimeter-wave radar has become an indispensable sensor in the field of environmental perception due to its advantages of all-weather operation, high ranging accuracy, and relatively low cost [1]. However, in practical applications, pedestrian detection and tracking in low signal-to-noise ratio (SNR) scenarios still face numerous challenges. When multiple radar systems operate simultaneously, they may interfere with each other, leading to increased noise floors, degraded signal quality, and subsequently affecting the accurate detection and stable tracking of pedestrian targets [2]. This phenomenon can result in a reduced SNR of the target signal [3], causing weak target signals to be submerged in noise, making it difficult to effectively identify pedestrian targets in complex traffic environments, and further increasing the difficulty of detection and tracking [4]. Therefore, achieving accurate and reliable detection and tracking of pedestrians is crucial for ensuring traffic safety.

Many scholars at home and abroad have conducted in-depth research on the issue of radar system interference. In literature [5], the authors meticulously analyzed the mutual interference phenomenon between FMCW-FMCW frequency-modulated millimeter-wave radars and classified the types of interference into coherent and non-coherent interference based on differences in radar parameters. The problem of increased noise due to interference poses a severe challenge to tracking methods such as Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) [6-7]. Particle filter, as a recursive Bayesian filtering algorithm based on the Monte Carlo method, approximates probability distributions by simulating a large number of particles and can globally search for the target's position, demonstrating strong adaptability and robustness in low SNR scenarios [8].

This paper proposes a particle filter method for low SNR scenarios. Firstly, by modeling the detection principle of the radar system, the principle of interference generation is identified. Secondly, the particle filter method is utilized to achieve global target search, thereby effectively estimating the target position. Finally, a pedestrian target tracking framework based on particle filtering is designed to achieve continuous and stable tracking of pedestrian target trajectories.

In summary, the core contributions of this paper can be refined into the following three aspects:

- (1) Systematically exploring the radar detection principle and clearly pointing out the impact of interference on radar signals poses severe challenges to subsequent target detection and tracking processes.
- (2) Proposing a method that utilizes particle filtering for global target search to effectively estimate the target position, significantly enhancing target tracking performance in low SNR scenarios.
- (3) This paper rigorously tests the proposed algorithm using a Multiple Input Multiple Output (MIMO) millimeter-wave radar platform. The experimental results fully demonstrate the stability and efficiency of the algorithm under complex interference conditions, further confirming its potential and value in practical applications.

2. RADAR INTERFERENCE SIGNAL MODEL

In real-world scenarios, FMCW radar systems not only receive normal target echo signals but are also prone to receiving radio frequency signals emitted by other radar systems. The signal model will be detailed in the following text.

In common FMCW radars, the transmission signal from the transmitting antenna (Tx) consists of K consecutive chirp signals with a period of T , which can be expressed as:

$$s(t) = \sum_{k=0}^{K-1} x(t - kT) \quad (1)$$

For a specific single chirp signal, its expression is:

$$x(t) = e^{j\varphi(t)} \text{rect}_T(t), \varphi(t) = 2\pi(f_c t + 0.5\alpha t^2). \quad (2)$$

In this equation, $\alpha = B/T$ represents the frequency modulation rate of the chirp signal, B denotes the sweep bandwidth, f_c is the carrier frequency, and $\text{rect}_T(t)$ represents a square wave signal with a duration of T and a normalized amplitude of 1, which is used to define the effective duration of the chirp signal.

When there are targets within the radar's detection range, the data model for the k th chirp signal captured by the receiving antenna (Rx) can be expressed as:

$$r_k(t) = \gamma x(t - \tau) + w_k(t) \quad (3)$$

Where $w_k(t)$ is the measurement noise. $\tau = 2R/c$ denotes the time delay experienced by the transmitted signal after being reflected by the target and received by the Rx antenna, which is directly related to the distance R between the target and the radar. γ represents the signal strength reflected back by the target, Controlled by the Friis transmission formula and the radar equation [9]:

$$|\gamma|^2 = \frac{PG_{rx}\sigma\lambda^2}{(4\pi)^3 d^4} \quad (4)$$

To extract valuable information from the received signal, we apply decoding techniques by blending the received signal $r_k(t)$ with the conjugate of the transmitted signal $x(t)$. This blending process results in a beat signal, whose mathematical representation is given by:

$$y_k(t) = r_k(t)x^*(t) = \gamma e^{-j2\pi(2\alpha\frac{R}{c}t + 2f_c\frac{R}{c} - 2\alpha(\frac{R}{c})^2)} \text{rect}_T(t - \frac{2R}{c}) + w_k(t)x^*(t) \quad (5)$$

In addition, FMCW radars utilize multiple consecutive chirp pulses for velocity estimation. Due to target motion, the velocity difference between different chirps causes a phase difference in $\exp\{j2\pi f_d kT\}$, where k is the serial number of the chirp pulse, $0 \leq k \leq K-1$. and $f_d = 2v/\lambda$ are related to the Doppler shift, v represents the target's velocity, and λ is the radar wavelength.

Meanwhile, for convenience in processing, we rearrange the data into a slow-time and fast-time data matrix, where n denotes the sample sequence number within a chirp, and k denotes the chirp signal number. The beat signal can be expressed as:

$$y_{k,n} = \gamma e^{-j2\pi(2\alpha\frac{R}{c}nTs + 2f_c\frac{R}{c} - 2\alpha(\frac{R}{c})^2)} * e^{j2\pi f_d kT} + w_{k,n} \quad (6)$$

Similarly, because the radar has multiple receiving antennas, there is $\exp\{j2\pi d \sin \theta / \lambda\}$ phase difference of magnitude between the radar signals received by adjacent antennas. d represents the antenna spacing, and θ represents the target azimuth. Therefore, the beat signal can be further written as:

$$y_{k,n} = \gamma e^{-j2\pi(2\alpha\frac{R}{c}nTs + 2f_c\frac{R}{c} - 2\alpha(\frac{R}{c})^2)} * e^{j2\pi f_d kT} * e^{j2\pi\frac{d \sin \theta}{\lambda}} + w_{k,n} \quad (7)$$

However, due to the emission of electromagnetic wave signals by other radars, this results in a large amount of clutter in the radar data, leading to a reduction in signal-to-noise ratio. As shown in the range-Doppler spectrum in Figure 1, the noise in the range-Doppler plot, which is interfered by other radars, is significantly increased.

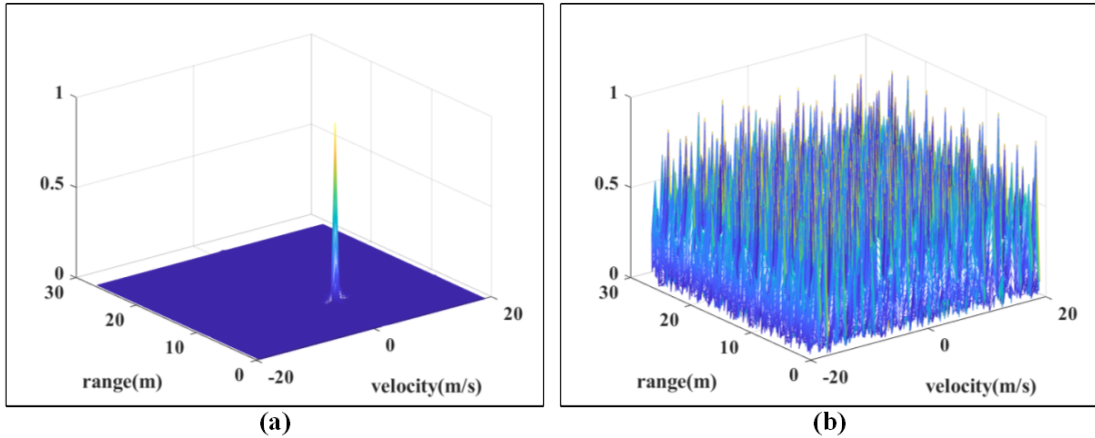


Figure 1. Range-Doppler spectrum (a) without interference; (b) with interference.

3. PEDESTRIAN TARGET TRACKING METHOD

3.1. Construction of Pedestrian Target Models

3.1.1. State Equation of Pedestrian Target.

Assuming the target exists in the radar measurement space, its motion state at time k can be represented as $s_k = [x_k, y_k, \dot{x}_k, \dot{y}_k]^T$, where (x_k, y_k) and (\dot{x}_k, \dot{y}_k) denote the position and velocity

magnitude of the target in the Cartesian coordinate system, respectively. Therefore, the motion process of the target over consecutive time intervals can be described as:

$$s_k = Fs_{k-1} + \Omega_k \quad (8)$$

Where Ω_k is the process noise, F denotes the state transition matrix, T represents the time interval between each frame of radar data, and then F is expressed as:

$$F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (9)$$

3.1.2. Measurement Equation of Radar System.

Due to the limitation of the radar system's perspective, the data it observes include distance, speed, and azimuth angle. Therefore, the measurement equation is as follows:

$$z_k = h(s_k) + w_k \quad (10)$$

Where $h(s_k)$ is the observation function, w_k is the measurement noise which follows a Gaussian distribution with parameters given by $N(0, \sigma^2)$. Due to the nonlinearity of the radar system, equation $h(s_k)$ can be represented as follows:

$$\begin{cases} r_k = \sqrt{(x_k)^2 + (y_k)^2} \\ v_k = (x_k \dot{x}_k + y_k \dot{y}_k) / \sqrt{(x_k)^2 + (y_k)^2} \\ \theta_k = \arctan(y_k/x_k) \end{cases} \quad (11)$$

3.2. Pedestrian Target Tracking Method

3.2.1. Framework of Particle Filter Algorithm.

According to the basic formula of Bayesian filtering [10]:

$$p(s_k | z_{1:k}) = \frac{p(z_k | s_k) \int p(s_k | s_{k-1}) p(s_{k-1} | z_{1:k-1}) ds_{k-1}}{p(z_k | z_{1:k-1})} \quad (12)$$

Where, $p(s_k | z_{1:k})$ represents the posterior probability of target state s_k given the observation data z_k , $p(z_k | s_k)$ is the observation model, $p(s_k | s_{k-1})$ is the state transition model, and $p(z_k | z_{1:k-1})$ is the normalization factor.

Particle filtering approximates the posterior probability $p(s_k | z_{1:k})$ using Monte Carlo methods, meaning that it estimates the target state by sampling s_k^i . The method for estimating the target state \hat{s}_k is as follows:

$$\hat{s}_k = E[s_k] = \int s_k * P(s_k | z_{1:k}) ds_k \approx \frac{1}{N} \sum_{i=1}^N s_k^i \quad (13)$$

Where N represents the number of samples. In this context, each sample has a weight denoted by $q_k^i = 1/N$. However, in practical scenarios, it is challenging to sample directly from the true likelihood distribution. Therefore, sequential importance sampling (SIS) is employed here, and the weight for each sample can be represented as:

$$q_k^i \propto \frac{p(z_k | s_k^i) p(s_k^i | s_{k-1}^i)}{q(s_k^i | s_{1:k-1}^i, z_{1:t})} q_{k-1}^i = p(z_k | s_k^i) q_{k-1}^i \quad (14)$$

Based on the measurement equation, the measurement likelihood function can be obtained as:

$$p(z_k | s_k^i) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{(z_k - h(s_k^i))^2}{2\sigma^2}\right\} \quad (15)$$

3.2.2. Algorithm Flow.

To overcome the challenges of pedestrian tracking in low signal-to-noise ratio environments, the Sequential Monte Carlo algorithm is applied to Bayesian state estimation [11].

Firstly, in the initialization phase, N samples are randomly generated and initialized. The initialization state is set to a random state within the measurable area.

Then, use formula (15) to calculate the importance weight q_k^i for the corresponding sample.

After computing the weights for the N samples, the weights are normalized $q_k^n = \tilde{q}_k^n / \sum_{n=1}^N \tilde{q}_k^n$, and resampling is performed based on the magnitude of each sample's weight to obtain a new set of samples \hat{s}_k^n . After resampling, each sample has an equal weight $1/N$.

The final target state estimate is then given by $\hat{s}_k^n = \frac{1}{N} \sum_{n=1}^N \mu \hat{s}_k^n$.

4. EXPERIMENTAL VERIFICATION

In this section, the tracking performance of the proposed algorithm under interference intensity is tested using simulation data, and compared with the Extended Kalman Filter (EKF). Finally, the effectiveness of the proposed method is further verified in practical scenarios using TI's AWR2243 cascaded radar system as the victim radar and the AWR1642 millimeter-wave radar system as the interfering radar.

4.1. Simulation Testing

This experiment verifies the tracking performance of the proposed method in low signal-to-noise ratio (SNR) scenarios by comparing the target tracking effects under different interference intensities. Here, the interference intensity is controlled primarily by adjusting the relative distance between the victim radar and the interfering radar. As seen in Figures 2(a1) and (b1), when the radar system is not interfered with, the Extended Kalman Filter (EKF) method slightly underperforms compared to the proposed method in terms of tracking performance. When the radar system is subjected to low-intensity radar interference, with an SNR=-10dB, Figures 2(a2) and (b2) show that the measured trajectories begin to deviate significantly. Due to this deviation, the tracking performance of the EKF method decreases significantly, while the performance of the proposed method remains almost unaffected. According to Figures 2(a3) and (b3), as the radar interference intensifies, specifically when the radar system is subjected to high-intensity radar interference with SNR=-20dB, the EKF method almost completely fails to track the target, whereas the tracking effect of the proposed method remains at a good level. This demonstrates the effectiveness of the proposed method.

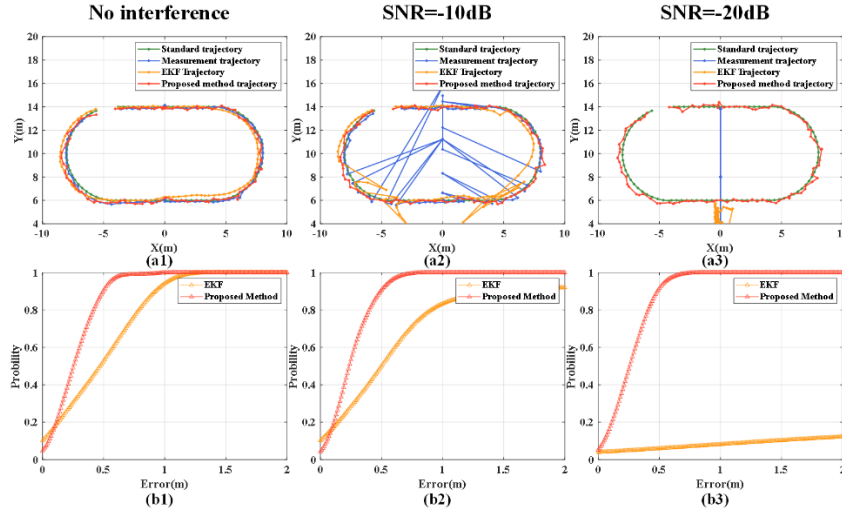


Figure 2. Tracking results at different SNR between radars

4.2. Real-World Scenario Testing

This experiment evaluates the tracking performance of the proposed method in an actual radar experiment scenario. The interfering radar is placed 3 meters away from the victim radar, with an angle of -45° relative to the y-direction. As shown in Figure 3(a), the radar interference results in increased noise in the 2D scan image of the radar. The trajectory plot is shown in Figure 3(b), where the increased background noise leads to information loss and false alarms, causing drift in the measured trajectory, the EKF tracking trajectory. However, the proposed method demonstrates better tracking performance due to its use of radar data without thresholds, as evidenced by the error distribution plot in Figure 3(c).

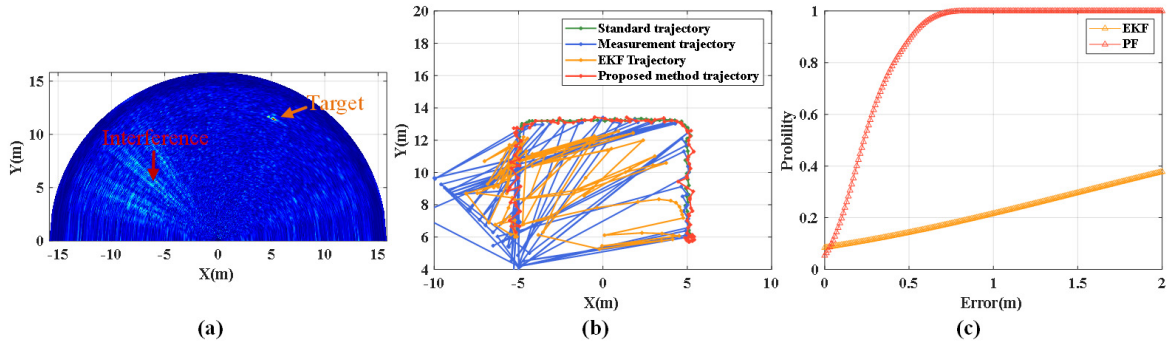


Figure 3. Tracking results in real radar interference scenario

5. CONCLUSION

This paper proposes a method for pedestrian target tracking in low SNR scenarios. Firstly, the impact of radar interference is analyzed in detail by establishing a radar detection model. Secondly, the particle filter method is employed to effectively address the target tracking issues caused by increased background noise, leveraging the characteristics of simulating a large number of particles to approximate the probability distribution. Finally, a pedestrian target tracking framework based on particle filtering is designed, achieving continuous and stable tracking of pedestrian target trajectories. Simulation and experimental results show that the algorithm proposed in this paper outperforms classical target tracking methods in low signal-to-noise ratio scenarios, with superior accuracy and robustness.

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