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Millimeter Wave Radar Target Tracking Based on Adaptive Kalman Filter

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Abstract—**With the continuous development of the intelligent transportation industry, target tracking has become an important research direction. Under normal circumstances, due to the complex road environment and changing backgrounds, millimeter wave radar has more interference when detecting targets. In addition to the variety of targets in the road and the different scattering intensity of multiple parts, the interference of the flicker noise on the radar must be considered. The combination of these noises can affect the accuracy of radar measurement and even make the radar to lose the target for a short time. The paper constructs a target tracking model based on adaptive Sage-Husa Kalman filter algorithm to track radar signals. The algorithm can not only estimate the real-time state of the system, but also estimate and modify the parameters of the system and the statistical parameters of the noise, so that the system model is closer to the current real state of the system, thus improving the accuracy of the target tracking. Even if radar loses its target in a short time, the target tracking model can estimate the approximate value of the true value of the target. The experimental results show that this method can track the radar target accurately and estimate the position information of the lost target.**

I. INTRODUCTION

With the continuous development of the intelligent transportation industry, intelligent obstacle detection has become an important research direction. Intelligent obstacle detection is the premise of automatic driving and intelligent driving safety assistance system. The core of obstacle detection is to tracking target quickly and accurately. According to the classification of target tracking sensors, the commonly used methods are machine vision, radar, ultrasonic and infrared [1]-[3]. Among them, radar is mainly divided into two types: laser and millimeter wave (MMW) radar [4], [5].

Due to its wide detection range, strong penetration performance and small size, MMW radar has been widely used in vehicle radar [6]. When the MMW radar is used to track target in the road environment, the radar is easily affected by the electromagnetic interference from the complex and changeable road environment, which results in the random noise in the target measurement [7]. In addition, according to the principle of millimeter wave radar measurement, considering the wide variety of the road target itself and the different scattering intensity of the target parts, the radar may be disturbed by the flicker noise [8]. These noises can affect the accuracy of radar measurements and may even make the radar to lose the target for a short time. In order to address this issue, target tracking algorithms are designed to reduce the impact of noise for the radar, thereby improving the accuracy of target tracking. At present, the most widely used target tracking algorithm is the Kalman filter algorithm [9]. However, the noise interference from the radar working in the road environment is complex and changeable. It is difficult to achieve high filtering accuracy by using an ordinary Kalman filter [10].

The paper compares several common filtering algorithms and propose a novel road target tracking method based on adaptive Sage-Husa Kalman. This method can not only improve the accuracy of radar, but also estimate the information of the lost target when the radar loses its target. The paper first analyzes the research status of target tracking, then builds the flicker noise model and designs a target tracking algorithm for millimeter wave radar signals. Finally, a multi-scene experiment is designed to verify the accuracy of the target tracking algorithm.

II. RESEARCH STATUS ON TARGET TRACKING

It is necessary to predict the state of the system from the measured data containing noise. A certain algorithm is needed to conduct such the prediction. The task of target tracking is to estimate and predict the state of the target through the data association algorithm and the filtering algorithm. The Principium chart of target tracking is shown in Fig.1 [11]. In Fig.1, the hollow circle represents the measured position of the target, the solid circle represents the filtering position, and the triangle represents the predicted position of the target. The rectangular window is called "Wave Gate". The filtering algorithm is used to get the predicted position of the target, and the measured position is corrected. Finally, the target filtering position is obtained, so as to realize the function of tracking the moving target. The dotted line in the figure represents the tracking process of the target, and the real line represents the trajectory of the target after the filtering.

In order to address the issue in Fig.1, various algorithms are developed. Among them, recursive Bayesian filtering theory was often used. For the filtering in complex environment, the traditional recursive Bayesian filtering theory is no longer applicable because of huge amount of computation. To this end, it made a great deal of suboptimal approximation methods. Commonly used suboptimal approximation methods are mainly Analytical Approximation and Sampling Approximation.

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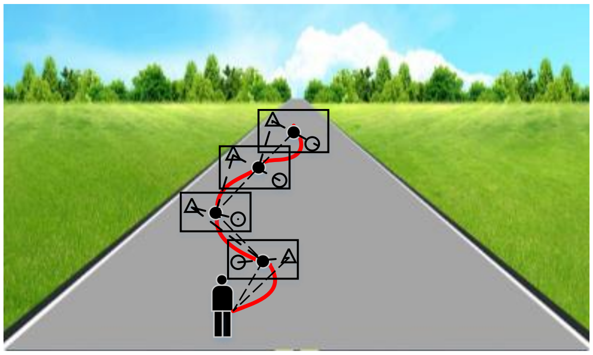


Fig.1 Principium chart of target tracking

A. Analytical Approximation Filter

The most typical analytical approximation method is the Extended Kalman Filter (EKF). EKF linearizes nonlinear problems by using first-order Taylor approximation and ignoring higher-order terms. EKF is a suboptimal filtering algorithm using the theory of linear filtering to solve nonlinear filtering problems. Reference [12] used a joint probabilistic data association EKF to solve the radar multi target tracking problem. In [13], an accurate continuous discrete EKF based on global error control ODE solver was used to deal with the radar target tracking problem. Experiments showed that this method had better flexibility and robustness. However, there was a large moment approximation error and computational cost. Due to the neglect of higher-order terms, EKF can cause large errors in the system, even unstable. In addition, in the actual environment, the flicker noise interference of the target also attenuates the filtering performance of EKF. Therefore, it is very difficult for this filtering algorithm to achieve the desired target tracking precision in flicker noisy environments. The EKF algorithm is simple, low computational complexity, but shows low precision and slow convergence speed.

B. Sampling Approximation Filter

Considering the probability density distribution of the approximate nonlinear function is easier than approximate non-linear function, more attention has been paid to using sampling methods approximate posterior probability distribution to solve the non-linear system state estimation problems [14]. The mainstream methods of sampling approximation are Unscented Kalman Filter (UKF) and Particle Filter (PF).

The principle of UKF is to take some points according to a certain rule in the original state distribution and make the mean and covariance of these points equal to the mean and covariance of the original state distribution. Substituting these points into the non-linear function, the corresponding set of non-linear function points is obtained, and then the mean and covariance are obtained by these points set. The resulting function values are not linearized and do not neglect their higher-order terms, so the estimation of the mean and covariance obtained from this method is more accurate than the EKF method. However, its disadvantage is that the calculation is large and it is difficult to apply to practical engineering. In [15], an Unscented Extended Kalman Filter algorithm was proposed. In each step of EKF, the Unscented Transform was run simultaneously to obtain a certain sample, and then the nonlinear posterior mean and posterior covariance were obtained. Although this method reduces the computational complexity of EKF, the accuracy was not significantly improved compared to UKF.

PF is a recursive Bayesian filter based on Monte Carlo method [16]. The basic idea is to find a set of random samples in the state space to approximate the conditional posterior probability density, so as to obtain the minimum variance estimation of the state. The PF can process non-linear data measured by non-Gaussian noise through a distribution of multiple samples (particles). The computational complexity of PF increases with the increase of the number of interest points. As time goes by, PF is also at risk of particle scarcity.

Reference [17] used particle filtering to track infrared targets. The method adopts the method of stratified sampling, and uses two complementary appearance models to solve the influence of appearance transformation and drastic abrupt motions on the target tracking. However, the method was lack of adaptability and stability. Reference [18] used radar and machine vision fusion to detect pedestrians and designs a particle filter to track the target. The method used the sample diversity improvement program to solve the sample shortage problem. However, the tracking accuracy of the method increased with the increase of particles, accompanied by a huge amount of computation.

C. Kalman Filter

Currently, the common radar target tracking algorithms in engineering applications include α-β filter [19], [20] and Kalman filter [21], [22]. Among them, Kalman filter algorithm is a high efficiency and widest filtering method.

The α-β filter is mainly used for the steady state filtering of the uniform motion trajectories, and the tracking effect of the maneuvering target is not satisfactory. Reference [19] proposed an adaptive α-β filtering algorithm based on a fuzzy principle [19]. This method used the standardized new interest and its first differential as the input variable, and introduces the time and speed factors to obtain the filter parameters adaptively. The filtering performance was better, but the algorithm was more complex. Based on α-β filtering, [20] proposed a boundary filtering strategy to achieve smooth filtering, and verified the effectiveness of the algorithm in navigation control [20]. However, this method was difficult to adapt to the complex and changeable movement.

Kalman filtering uses an optimized autoregressive algorithm to obtain the optimal value of state estimation through multiple recursive operations. The Kalman filter equation is as shown in (1).

$$
\begin{aligned}
&\hat{X}(k|k-1) = \Phi(k|k-1) * \hat{X}(k-1|k-1) \\
&\hat{X}(k|k) = \hat{X}(k|k-1) + K(k)\big[Z(k) - H(k) * \hat{X}\big] \\
&K(k) = P(k|k-1)H(k)^T / [H(k)P(k|k-1)H(k)^T] \\
&P(k|k-1) = \Phi(k|k-1)P(k-1|k-1)\Phi(k|k-1)^T + \\
&\qquad GQ(k-1)G^T \\
&P(k|k) = [I - K(k)H(k)] * P(k|k-1)
\end{aligned} \tag{1}
$$

In (1), $\hat{X}(k|k)$ is the optimal estimation value at the k moment.

Reference [21] combined Kalman filter and tracking learning detection algorithms to achieve target detection and tracking in complex scenes. This method aimed at the maneuvering target in the video image, first used the Kalman filter and the tracking learning detection algorithm to estimate the approximate area of the target, and then carried on the detection to the target area, thus improves the target detection speed. In [22], a non-linear Sage-Husa random weighted unscented Kalman filter algorithm was proposed to improve the resolution of combined navigation, but the algorithm had poor adaptability. Reference [23] used MMW radar and machine vision to detect obstacles, and used adaptive Kalman filter to achieve the target tracking. However, there was no description of the true trajectory of the target.

III. Design of Radar Target Tracking Algorithm

A. *Road Target Tracking Model*

Assume that a target is moving at a steady speed in the road, the motion state of the target can be described as:

$$\begin{aligned} X(k) &= \Phi(k|k-1) * X(k-1) + W(k) \\ Z(k) &= H(k) * X(k) + V(k) \end{aligned} \tag{2}$$

$X(k)$ is the state vector. $\Phi(k|k-1)$ is the state transition matrix. $W(k)$ is the system process noise, which is Gaussian white noise with mean zero. $Z(k)$ is the measurement vector. $V(k)$ is the measurement noise, which is Gaussian white noise with mean zero. $H(k)$ is the measurement matrix.

Select the system state vector $X = [r, r_v, l, l_v]^T$, the measurement vector can be written $Z = [r, l]^T$. Among them, r and l are the target longitudinal and lateral relative distances; r_v and l_v are the target longitudinal and lateral relative velocity. Then the system measurement equation can be expressed as in (3).

$$Z(k) = \begin{bmatrix} r(k) \\ l(k) \end{bmatrix} + V(k) \tag{3}$$

According to the flicker noise model in [24], the flicker noise is constructed by weighting Gaussian noise with mean μ_1 and μ_2 and variance S_1 and S_2 [24]. The probability density function of flicker noise can be expressed as in (4).

$$p(\omega) = (1-\lambda)N(\omega; \mu_1; S_1) + \lambda N(\omega; \mu_2; S_2) \tag{4}$$

In (4), $N(\omega; \mu_i; S_i)$ represents the probability density of Gauss distribution at ω with mean value of μ_i and the variance of S_i. The first moment and the second moment of flicker noise obtained by moment matching method are as shown in (5).

$$\begin{aligned} \mu &= E[\omega] = (1-\lambda)\mu_1 + \lambda\mu_2 \\ S &= E[(\omega-\mu)(\omega-\mu)^T] = (1-\lambda)S_1 + \lambda S_2 + \\ &\quad (1-\lambda)\mu_1\mu_1^T + \lambda\mu_2\mu_2^T - \mu\mu^T \end{aligned} \tag{5}$$

Fig. 2 shows the probability density distribution of flicker noise generated by the weighted sum of two Gaussian noise with different variances. The left two images are Gaussian noise with different variances, and the right image is flicker noise.

When the radar is disturbed by flicker noise at certain moments, the random noise covariance matrix and observation noise covariance matrix given by the system modeling will have a certain deviation from the actual noise interference of the system. At this time, it is difficult for ordinary Kalman filter to achieve high target tracking

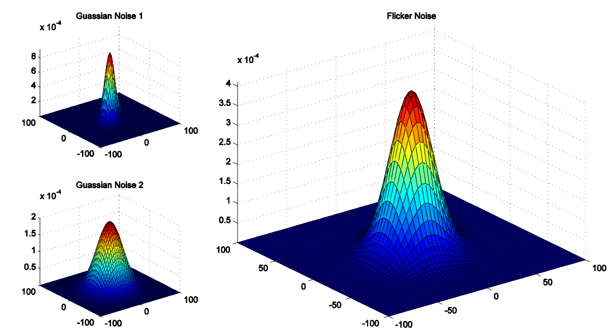


Fig. 2 Probability density distribution of flicker noise

accuracy. The adaptive Kalman filter introduces a mechanism in the algorithm that can adjust the system parameters in time according to the measured data, so that the system model can be closer to the real state of the system. However, adaptive Kalman filter is different, it can adjust the noise parameters in the system model according to the actual measurement values, so that the system model is closer to the current real state of the system, so as to compensate for the interference caused by flicker noise to the system. The most commonly used methods of adaptive Kalman filter are maximum likelihood, Bayes, covariance matching and Sage-Husa methods. In the Sage-Husa methods, the fading memory index weighted sequence and innovation sequence are introduced, which can realize statistical system noise and observation noise while estimating the current state of the system. The Sage-Husa method is simple and easy to implement. Therefore, we choose adaptive Sage-Husa Kalman filter in the paper.

B. *Tracking Algorithm Based on Adaptive Sage-Husa Kalman Filter*

Assume that the system state vector is $X = [r, r_v, l, l_v]^T$ and the target state at time k is $X(k) = [r(k), r_v(k), l(k), l_v(k)]^T$. If the system measurement cycle is T, then the state of the target transferred from state k-1 to state k can be expressed as in (6).

$$\begin{aligned} r(k) &= r(k-1) + r_v(k-1) * T + w_r(k) \\ l(k) &= l(k-1) + l_v(k-1) * T + w_l(k) \end{aligned} \tag{6}$$

Converting (6) into a matrix calculation form, as shown in (7).

$$\begin{aligned} \begin{bmatrix} r(k) \\ r_v(k) \\ l(k) \\ l_v(k) \end{bmatrix} &= \begin{bmatrix} r(k-1) + r_v(k-1) * T \\ r_v(k-1) \\ r(k-1) + r_v(k-1) * T \\ r_v(k-1) \end{bmatrix} + W(k) = \\ &\begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} r(k) \\ r_v(k) \\ l(k) \\ l_v(k) \end{bmatrix} + W(k) \end{aligned} \tag{7}$$

Combining (7) with (2), we can get:

$$\begin{aligned} X(k) &= \Phi(k|k-1) * X(k-1) + W(k) = \\ &\begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} * X(k-1) + W(k) \end{aligned} \tag{8}$$

Then the state transition matrix is calculated by using (8).

$$\Phi(k|k-1) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

Combined with initial state $\hat{X}(0)$ and measurement value $Z(k)$, we can get the optimal state of the system estimates. In this method, the system process noise and observation noise are considered unchanged. Obviously, there is a shortage of such treatment. The adaptive Sage-Husa Kalman filter can constantly update the noise covariance according to the previous data to better adapt to the current measurement environment. The adaptive Kalman filter needs to set initial parameters, as shown in (10).

$$H(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \Phi(k|k-1) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$R(k) = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.013 \end{bmatrix}, \quad \hat{Q}(0) = 0.5, \quad P(0) = I \tag{10}$$

Using the set parameters and initial values into the adaptive Kalman filter equation as follows:

$$\hat{X}(k|k-1) = \Phi(k|k-1)\hat{X}(k-1) \tag{11}$$

$$\varepsilon(k) = Z(k) - \hat{X}(k|k-1)) \tag{12}$$

$$\varepsilon(k)\varepsilon^T(k) \leq \xi * Tr\,[H(k)\,P(k-1)H^T(k) + R(k) \tag{13}$$

If (13) is true, we have:

$$S(k) = 1 \tag{14}$$

Otherwise:

$$S(k) = \frac{Tr\left[\varepsilon(k)\varepsilon^T(k) - H(k)G\hat{Q}(k-1)G^T H^T(k) - R(k)\right]}{Tr\,[\varepsilon(k)\varepsilon^T(k) - H(k)G\hat{Q}(k-1)G^T H^T(k) - R(k)} \tag{15}$$

$$P(k|k-1) = S(k)\Phi(k|k-1)P(k-1)\Phi^T(k|k-1) + G\hat{Q}(k-1)G^T \tag{16}$$

$$S(k) = \frac{P(k|k-1)H^T(k)}{H(k)P(k|k-1)H^T(k) + R(k)} \tag{17}$$

$$\hat{X}(k) = X(k|k-1) + K(k)\varepsilon(k) \tag{18}$$

$$P(k) = [I - K(k)H(k)P(k|k-1)) \tag{19}$$

$$d(k-1) = (1-b)/(1-b^k) \tag{20}$$

If $G\hat{Q}(k-1)G^T$ is positive semi-definite matrix, we have:

$$G\hat{Q}(k-1)G^T = [1-d(k-1)]G\hat{Q}(k-1)G^T + d(k-1)[K(k)\varepsilon(k)\varepsilon^T(k)K^T(k) + P(k) - \Phi(k|k-1)P(k-1)\Phi^T(k|k-1)] \tag{21}$$

Otherwise, we have:

$$G\hat{Q}(k-1)G^T = [1-d(k-1)]G\hat{Q}(k-1)G^T + d(k-1)[K(k)\varepsilon(k)\varepsilon^T(k)K^T(k) + P(k) \tag{22}$$

Among them, b is called the forgetting factor. $d(k-1)$ is the fading memory index weighted sequence and $\varepsilon(k)$ is the new information sequence. Tr is the trace of matrix.

IV. EXPERIMENT

A. Verification of Algorithm Model

(i) Hardware equipment: Delphi ESR 76GHz MMW radar, Kvaser Leaf Light V2 Can card, PC, UPS, UAV, radar bracket, tape and a number of experimenter, as shown in Fig.3.

(ii) Software platform: Windows7, Microsoft VS, SQL Server, MATLAB.

(iii) Experiment procedure:

(1) Establish the radar coordinate system, take the radar geometry center as the origin. The R axis points to the front of the radar and the L axis points to the right side of the radar, as shown in Fig.4.

(2) Single target and multiple targets make straight or curvilinear motion in front of radar.

(3) The system obtained position information and speed information of the forward maneuvering target.

In order to verify the tracking performance of adaptive Kalman filter for different maneuvering targets, a total of four different scenes are listed in this paper, as shown in Table I.

TABLE I. SCENES DESCRIPTIONS

Scene number	Scene description
1	single target linear motion
2	single target "S" curve motion
3	multiple target parallel linear motion
4	multiple target "S" curve motion

Fig.5 and Fig.6 shows the different scenes. The filtering contrast of the target motion trajectory in different scenes shown in Fig.7-Fig.10.

Fig.3 Experimental hardware equipment

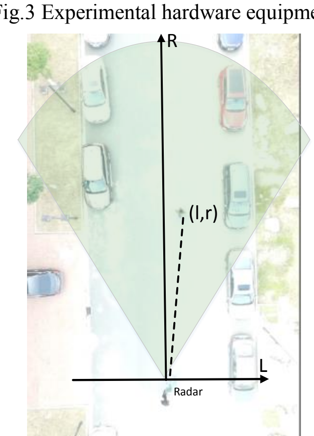


Fig.4 Radar coordinate system

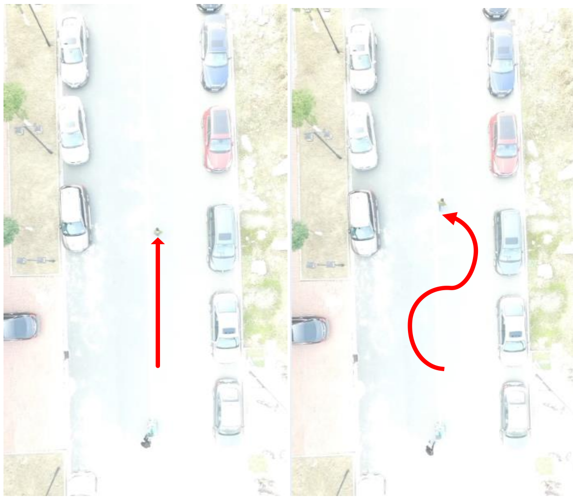


Fig.5 (a) Scenario 1 Fig.5 (b) Scenario 2

Fig.5 Single target motion

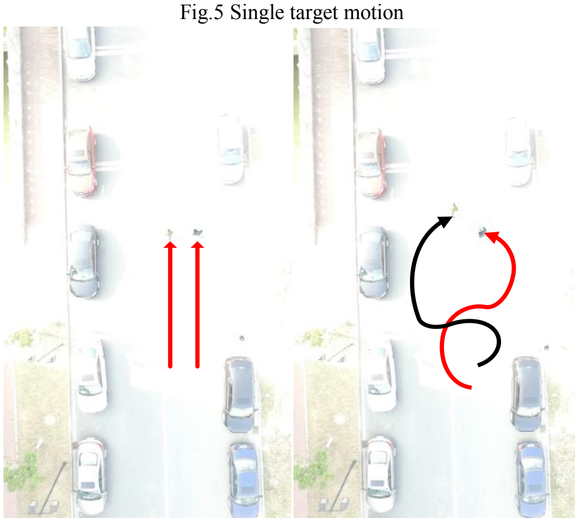


Fig.6 (a) Scenario 3 Fig.6 (b) Scenario 4

Fig.6 Multiple target motion

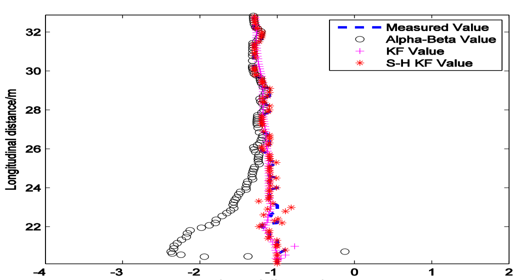
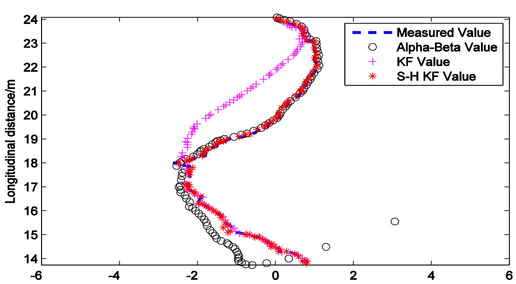


Fig.7 Scenario 1 filter contrast



\Fig.8 Scenario 2 filter contrast

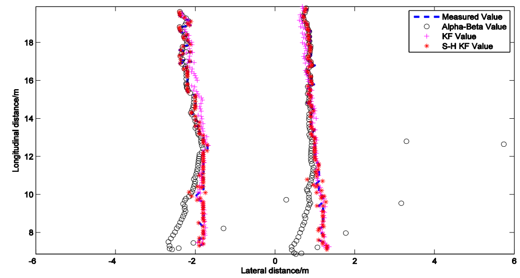


Fig.9 Scenario 3 filter contrast

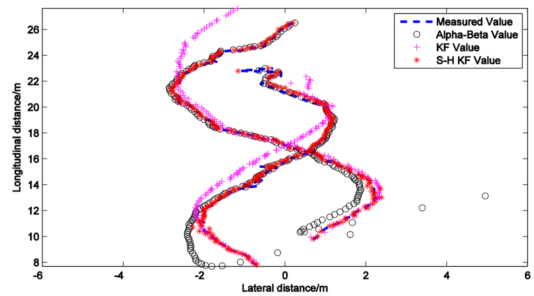


Fig.10 Scenario 4 filter contrast

As shown in Fig.7-Fig.10, the comparison results with the other two filtering methods showed that the adaptive Kalman filtering has higher accuracy and stability. Among them, the α-β filter converges slowly, while the ordinary Kalman filter appears the situation of filter divergence. More importantly, the adaptive filter algorithm can accurately estimate the position of the target in the presence of multiple maneuvering targets.

B. Estimation of Lost Target by Filtering Algorithms

Due to electromagnetic interference and flicker noise, MMW radar may cause transient loss of targets. Fig.12(a) shows the experimental data when the radar has lost the target for a short time; (b) is the experimental data when adding the target information estimated by the filtering algorithm. The blue point line is the true value, the black dotted line is the measured value, and the red line is the filter value. The data in the green box is the data when the radar lost the target. Therefore, there is no measurement in (a), only the real value and the estimated value.

Fig.12 shows that the position information of the lost target obtained by the filtering algorithm is close to the true value of the target and can be used to replace the real value of the target. In order to further verify the accuracy of the target information estimated by the filtering algorithm, we select data from a large number of experimental data for missing targets and estimates the missing target information. The experimental results are shown in Table II.

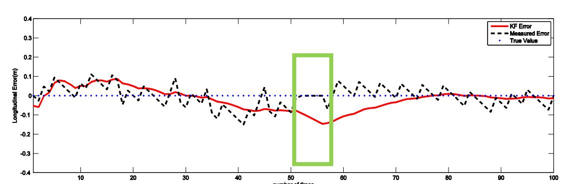


Fig.11 Longitudinal estimation when losing target

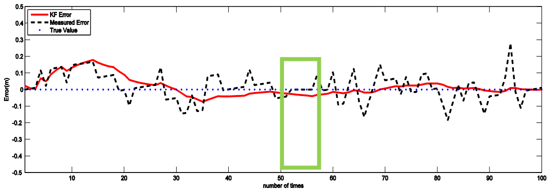


Fig.12 Lateral estimation when losing target

TABLE II. ERROR OF TARGET MADE UP OF DIFFERENT FILTER

Experimental scene	Longitudinal error of ordinary KF (m)	Longitudinal error of adaptive KF (m)	Lateral error of ordinary KF(m)	Lateral error of adaptive KF (m)
1	0.072	0.044	0.079	0.045
2	0.094	0.050	0.091	0.075
3	0.069	0.046	0.108	0.070
4	0.157	0.073	0.144	0.084
5	0.089	0.047	0.078	0.069
6	0.076	0.049	0.083	0.053
7	0.061	0.039	0.054	0.038
8	0.081	0.047	0.119	0.060
9	0.104	0.052	0.132	0.056
10	0.150	0.060	0.162	0.061
Mean value	0.095	0.051	0.105	0.061

It is easy to conclude from the experimental data in Table II that the target estimate estimated by the adaptive Kalman filter has higher accuracy than the ordinary Kalman filter. Therefore, when radar missed detection occurs, the estimated value can be used to approximate the target's true value.

V. CONCLUSION

In this paper, a target tracking algorithm based on adaptive Sage-Husa Kalman filter is proposed to solve the MMW radar target tracking problem in complex road environment. Firstly, a flicker noise model is constructed, then a filtering algorithm for tracking radar targets is designed and verified by real scenarios. Finally, aiming at the missing target phenomenon of MMW radar, the accuracy of target information estimated by the algorithm is verified. The experimental results show that this method can track the radar target accurately and solve the problem of radar missing target. In summary, the proposed method can improve the accuracy and reliability of the MMW radar, which will help the MMW radar to play a morefull role in the field of intelligent transportation.

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