

# Target Tracking based on Millimeter Wave Radar in Complex Scenes

Guangyao Zhai, Cheng Wu\*, Yiming Wang

*School of Rail Transportation, Soochow University, Suzhou, 215131, China*

---

## Abstract

Currently, the method of using millimeter wave radar to detect obstacles in front of vehicles has been widely used. When using millimeter wave radar to detect obstacles on the road, the radar has more noise interference due to the changeable road environment and complex background. Combined with the complexity and variety of road targets, the random changes of scattering intensity and relative phase of different parts cause the distortion of the echo phase wave, resulting in the flicker noise that affects the accuracy of measurement, and even lead to the loss of targets. In this case, there are some shortcomings in tracking the target using the ordinary Kalman filter algorithm. In this paper, a Sage-Husa adaptive Kalman filtering algorithm is designed for the road environment to track radar targets and improve the accuracy of target tracking. Then, the radar and machine vision information fusion method is used to intuitively judge the filtering effect and determine whether the radar loses the target. Finally, the true value of the target position is approximated by filtered value when the radar loses its target. The experimental results show that this method can improve the accuracy and reliability of the millimeter wave radar.

*Keywords:* millimeter wave radar; Kalman filter; target tracking

(Submitted on October 30, 2017; Revised on December 5, 2017; Accepted on January 23, 2018)

© 2018 Totem Publisher, Inc. All rights reserved.

---

## 1. Introduction

With the rapid formation of intelligent transportation industry, vehicle networking, automatic driving, intelligent driving safety assistance system have developed rapidly. Obstacle detection has become one of the most important research directions. At present, the typical obstacle detection methods mainly include machine vision, radar, ultrasound and infrared [1,10,18]. The radar can be divided into laser radar and millimeter wave (MMW) radar [2,16].

MMW radar has been widely used due to its small size, wide detection range, small weather impact and so on [5]. Due to the limitations of the MMW radar measurement principle and the external electromagnetic interference during use, the target measurement value obtained will contain random measurement noise, which will affect the accurate positioning of targets and even lead to the loss of targets [12]. Therefore, it is necessary to use the corresponding target tracking algorithm to assist MMW radar in obstacle detection. In addition, in the civil field, high precision and high stability radar have been limited due to the high cost of hardware. In this case, more attention has been paid to improving the software of the radar. The use of target tracking algorithm to improve the performance of the radar is the most commonly used method.

At present, there are a lot of literature on the theory of target tracking, of which the most widely used is the Kalman filter algorithm. Kalman filter is used to solve the problem that the system cannot get accurate measurement value because of random noise interference. Kalman filter eliminates random noise interference based on a set of observations and predicts as close as possible to the true value [7]. Aiming at the target in the complex road environment, the noise interference of radar is more complex and changeable. Ordinary Kalman filter cannot adapt to the complex noise environment, so there are some shortcomings in tracking the road target. Therefore, a road target tracking method based on Sage-Husa adaptive Kalman filter is proposed in this paper [15]. This method can not only improve the accuracy of the radar, but also make up for missing information when the radar loses its target.

\* Corresponding author.

E-mail address: [cwu@suda.edu.cn](mailto:cwu@suda.edu.cn)

## 2. Research status of target tracking

When it is necessary to predict the state of the system from the measured data containing noise, a certain algorithm is needed to predict the real state of the system from the data. The task of target tracking is to estimate and predict the state of the target through the data association algorithm and the filtering algorithm. For target tracking, the most commonly used algorithms are  $\alpha$ - $\beta$  filter [6,8], weighted least squares filter [4,17] and Kalman filter [3,9,14]. Among them, Kalman filter algorithm has a high efficiency and widest filtering method.

### 2.1. $\alpha$ - $\beta$ filter

The  $\alpha$ - $\beta$  filter is generally applicable to the uniform motion of the target. Assuming that a state vector is  $X = [x, \dot{x}]^T$ , in which  $x$  and  $\dot{x}$  are the target position and the velocity vector, respectively, then the target equation of state is as Equation (1):

$$\hat{X}(k|k) = \Phi(k|k-1)\hat{X}(k|k-1) + GW(k) \quad (1)$$

In Equation (1),  $\hat{X}(k|k)$  is the estimate of the system state at the  $k$  moment.  $\Phi(k|k-1)$  is the state transition matrix.  $G$  is the input relation matrix and  $W(k)$  is the process noise. The measurement equation is as Equation (2):

$$Z(k) = H(k)\hat{X}(k) + V(k) \quad (2)$$

In Equation (2),  $Z(k)$  is the measured value of the system at time  $k$ .  $H(k)$  is the measurement matrix and  $V(k)$  is the measurement noise. The filtering equation is as Equation (3)-(5):

$$\hat{X}(k|k-1) = \Phi\hat{X}(k-1|k-1) \quad (3)$$

$$\hat{X}(k|k) = \hat{X}(k|k-1) + K[Z(k) - H(k)\hat{X}(k|k-1)] \quad (4)$$

$$K = [\alpha, \beta/T]^T \quad (5)$$

Among them,  $K$  is the gain matrix. The  $\alpha$ - $\beta$  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. Document [8] uses fuzzy adaptive  $\alpha$ - $\beta$  filter to track targets, which performs better than traditional  $\alpha$ - $\beta$  filter [8]. However, its fuzzy logic rules have poor adaptability. In document [6], the estimated acceleration is introduced into the traditional  $\alpha$ - $\beta$  filter as input control quantity to track the maneuvering targets, which improves the tracking performance but lacks experimental verification in the actual scenario [6].

### 2.2. Weighted least squares filter

Suppose there is a system where the measurement noise is Gaussian white noise with mean zero and covariance matrix  $R(k)$ , while ignoring the effects of state noise. If the system state vector is  $X = [x, \dot{x}]^T$ , where  $x$  and  $\dot{x}$  are the target position and the velocity vector, respectively, the weighted least squares filter equations are Equations (6)-(9):

$$\hat{X}(k|k) = \hat{X}(k|k-1) + K(k)[Z(k) - H(k)\hat{X}(k|k-1)] \quad (6)$$

$$\hat{X}(k|k-1) = \Phi(k|k-1)\hat{X}(k-1|k-1) \quad (7)$$

$$K(k) = P(k|k-1)H^T(k)/R(k) \quad (8)$$

$$P(k|k) = P(k|k-1) - K(k)H(k)P(k|k-1) \quad (9)$$

$K(k)$ ,  $H(k)$ ,  $\Phi(k|k-1)$ ,  $P(k|k)$  and  $P(k|k-1)$  are filtering gain matrix, measurement matrix, state transition matrix, covariance matrix and prediction covariance matrix, respectively. Document [4] proposed a recursive model based on time difference measurement, and introduced the state equation constraint in Kalman filter to reduce the impact of random error on position accuracy [4]. However, the algorithm is complex and computationally intensive, which makes it difficult to meet the

real-time requirements. In Document [17], aiming at the shortage of prior information, the least squares criterion is used to increase the weighting factor of the sensor with small error so as to improve the tracking accuracy [17]. In view of radar targets, a certain number of statistical characteristics can be found from a large number of data, so as to obtain a certain prior knowledge. The use of weighted least squares filtering has no more advantages.

### 2.3. Kalman filter

The working principle of Kalman filter is to use the minimum mean square error estimate, and obtain the optimal value of state estimation through multiple recursive operations. The Kalman filter algorithm is optimal when the system satisfies the linear conditions and the measurement noise, and the system noise are independent Gaussian noise. The entire Kalman filter process is as Equations (10)-(14):

$$\hat{X}(k|k-1) = \Phi(k|k-1) * \hat{X}(k-1|k-1) \quad (10)$$

$$\hat{X}(k|k) = \hat{X}(k|k-1) + K(k)[Z(k) - H(k) * \hat{X}(k|k-1)] \quad (11)$$

$$K(k) = P(k|k-1)H(k)^T / [H(k)P(k|k-1)H(k)^T] \quad (12)$$

$$P(k|k-1) = \Phi(k|k-1)P(k-1|k-1)\Phi(k|k-1)^T + GQ(k-1)G^T \quad (13)$$

$$P(k|k) = [I - K(k)H(k)] * P(k|k-1) \quad (14)$$

Among them,  $\hat{X}(k|k)$  is the optimal estimation value at time  $k$ .

Document [3] used Kalman filter to track the target and locate it dynamically. The experimental results show that it has good filtering effect, but only limited to the theoretical level [3]. In Document [14], Kalman and particle filter are used to track radar targets. In most cases, the filtering effect is good, but it is difficult to meet the real-time requirements with a large amount of calculation [14]. Kalman filter is also used in the Document [9] to track radar targets. The proposed algorithm has a good filtering effect and is easy to implement. However, it lacks the verification of the accuracy of the tracking model and does not consider the target loss [9].

## 3. Design of radar target tracking algorithm

### 3.1. Road target tracking model

In the aspect of radar target tracking model, there is a commonly used constant velocity model, constant acceleration model and the current statistical model. Assuming there is a single target moving at a steady speed in the road, the motion state of the target can be described as Equations (15)-(16):

$$X(k) = \Phi(k|k-1) * X(k-1) + W(k) \quad (15)$$

$$Z(k) = H(k) * X(k) + V(k) \quad (16)$$

$X(k)$  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.

The target information obtained by the radar mainly includes target longitudinal relative distance  $r$ , longitudinal relative velocity  $r_v$ , lateral relative distance  $l$  and lateral relative velocity  $l_v$ . Select the system state vector  $X = [r, r_v, l, l_v]^T$ , the measurement vector  $Z = [r, l]^T$ , then the system measurement equation can be expressed as Equation (17):

$$Z(k) = \begin{bmatrix} R(k) \\ L(k) \end{bmatrix} + V(k) \quad (17)$$

Ordinary Kalman filter is often used for tracking air targets because of the single background and less interference. As for the road targets, due to the changeable road environment and complicated background, radar is much disturbed. There is a certain deficiency in tracking targets with the ordinary Kalman filter algorithm. Combined with the complexity and variety of road targets, the random changes of scattering intensity and relative phase of different parts cause the distortion of echo phase wave, resulting in the flicker noise that affects the accuracy of measurement [11].

According to the flicker noise model given in Document [13], the flicker noise is constructed by weighting Gaussian noise with mean  $\mu_1, \mu_2$ , and variance  $P_1$  and  $P_2$  [13]. The probability density function of flicker noise can be expressed as Equation (18):

$$p(\omega) = (1 - \lambda)N(\omega; \mu_1; P_1) + \lambda N(\omega; \mu_2; P_2) \quad (18)$$

In Equation (18),  $N(\omega; \mu_i; P_i)$  represents the probability density of Gauss distribution at  $\omega$  with mean value of  $\mu_i$  and the variance of  $P_i$ . The first moment and the second moment of flicker noise obtained by moment matching method are as Equation (19)-(20):

$$\mu = E[\omega] = (1 - \lambda)\mu_1 + \lambda\mu_2 \quad (19)$$

$$P = E[(\omega - \mu)(\omega - \mu)^T] = (1 - \lambda)P_1 + \lambda P_2 + (1 - \lambda)\mu_1\mu_1^T + \lambda\mu_2\mu_2^T - \mu\mu^T \quad (20)$$

Figure 1 shows the probability density distribution of flicker noise generated by the weighted sum of two Gaussian noise with different variances. Two of the dashed lines are Gaussian noise with different variances, and the solid line is flicker noise.

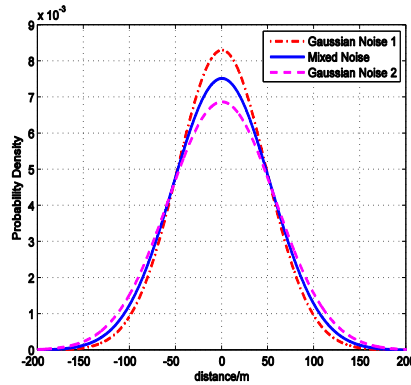


Figure 1. Probability density distribution of flicker noise

When using the ordinary Kalman filter to track the road targets, the random noise received by the radar contains a part of flicker noise, which leads to the random noise covariance matrix and the measurement noise covariance matrix given by the system modeling have a certain deviation with the actual system noise. Therefore, ordinary Kalman filter cannot better adapt to the tracking of road targets. The adaptive Kalman filter can estimate the system state vector in real time by recursive operation. At the same time, it estimates and corrects the unknown or uncertain system model parameters and noise statistical parameters. Commonly used adaptive Kalman filter methods include maximum likelihood method, covariance matching method, Bayesian method and Sage-Husa method. The most widely used is the Sub-optimal unbiased maximum a posteriori noise statistical estimator proposed by Sage and Husa [9]. This method can not only estimate the mean of the system noise matrix and the covariance of the measurement noise matrix, but also be easily calculated. In theory, Sage-Husa adaptive Kalman filter can better adapt to the tracking of road targets.

### 3.2. Tracking algorithm design based on Sage-Husa adaptive 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:

$$\begin{aligned} r(k) &= r(k-1) + r_v(k-1) * T + w_r(k) \\ l(k) &= l(k-1) + l_v(k-1) * T + w_l(k) \end{aligned} \quad (21)$$

Converting Equation (21) into a matrix calculation form:

$$\begin{bmatrix} r(k) \\ r_v(k) \\ l(k) \\ l_v(k) \end{bmatrix} = \begin{bmatrix} r(k-1) + r_v(k-1) * T \\ r_v(k-1) \\ r(k-1) + r_v(k-1) * T \\ r_v(k-1) \end{bmatrix} + W(k) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} r(k) \\ r_v(k) \\ l(k) \\ l_v(k) \end{bmatrix} + W(k) \quad (22)$$

Combining Equation (22) with Equation (15):

$$X(k) = \Phi(k|k-1) * X(k-1) + W(k) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} * X(k-1) + W(k) \quad (23)$$

Then the state transition matrix is obtained as Equation (24):

$$\Phi(k|k-1) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (24)$$

The ordinary Kalman filter usually assumes that the system measurement error and random noise statistics system are constant in order to facilitate the calculation. Combined with initial state  $\hat{X}(0)$ ,  $P(0)$  and measurement value  $Z(k)$  can get the optimal state of the system estimates. Obviously, there is a shortage of such treatment. The Sage-Husa adaptive Kalman filter can constantly update the noise covariance according to previous data to better adapt to the current measurement environment. The adaptive Kalman filter needs to set initial parameters, as shown below:

$$H(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \Phi(k|k-1) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} R(k) = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.013 \end{bmatrix}, \hat{Q}(0) = 0.5, \quad P(0) = I$$

The parameters and initial values are brought into the adaptive Kalman filter equation, and the entire filtering process is as Equations (25)-(33):

$$\hat{X}(k|k-1) = \Phi(k|k-1)\hat{X}(k-1) \quad (25)$$

$$\varepsilon(k) = Z(k) - \hat{X}(k|k-1) \quad (26)$$

$$\varepsilon(k)\varepsilon^T(k) \leq \xi * Tr [H(k) P(k-1)H^T(k) + R(k)] \quad (27)$$

$$S_k = \begin{cases} 1 & \text{Equation(27) is true.} \\ \frac{Tr[\varepsilon(k)\varepsilon^T(k) - H(k)G\hat{Q}(k-1)G^TH^T(k) - R(k)]}{Tr[\varepsilon(k)\varepsilon^T(k) - H(k)G\hat{Q}(k-1)G^TH^T(k) - R(k)]} & \text{Equation(27) is not true} \end{cases} \quad (28)$$

$$P(k|k-1) = S(k)\Phi(k|k-1)P(k-1)\Phi^T(k|k-1) + G\hat{Q}(k-1)G^T \quad (29)$$

$$K(k) = P(k|k-1)H^T(k)/[H(k)P(k|k-1)H^T(k) + R(k)] \quad (30)$$

$$\hat{X}(k) = \hat{X}(k|k-1) + K(k)\varepsilon(k) \quad (31)$$

$$P(k) = [I - K(k)H(k)P(k|k-1)] \quad (32)$$

$$d(k-1) = (1-b)/(1-b^k) \quad (33)$$

If  $G\hat{Q}(k-1)G^T$  is positive definite matrix as Equation (34):

$$G\hat{Q}(k-1)G^T = [1-d(k-1)]G\hat{Q}(k-1)G^T + d(k-1)[K(k)\varepsilon(k)\varepsilon^T(k)K^T(k) + P(k) - \Phi(k|k-1)P(k-1)\Phi^T(k|k-1)] \quad (34)$$

If  $G\hat{Q}(k-1)G^T$  is positive semi-definite matrix as Equation (35):

$$G\hat{Q}(k-1)G^T = [1-d(k-1)]G\hat{Q}(k-1)G^T + d(k-1)[K(k)\varepsilon(k)\varepsilon^T(k)K^T(k) + P(k)] \quad (35)$$

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

## 4. Experiments

### 4.1. Accuracy verification of algorithm model

In order to verify the accuracy of the algorithm model, this paper designed experiments to verify.

Hardware equipment:

Delphi ESR 76GHz MMW radar, Kavasr Leaf Light V2 Can card, PC, UPS, UAV, radar bracket, tape, a number of experimenters.

Software platform:

Windows7, Microsoft VS, SQL Server, MATLAB.

Experiment procedure:

First, the two-coordinate radar system is established. The  $R$  axis corresponds to the target longitudinal distance of  $R$ , and the  $L$  axis corresponds to the target lateral distance  $L$ , as shown in Figure 2. The radar detection system is then used for continuous detection of pedestrians moving ahead. The detection cycle of the system is 0.1s. The target information obtained by the system includes the longitudinal relative distance, the longitudinal relative velocity, the lateral relative distance and the lateral relative velocity.

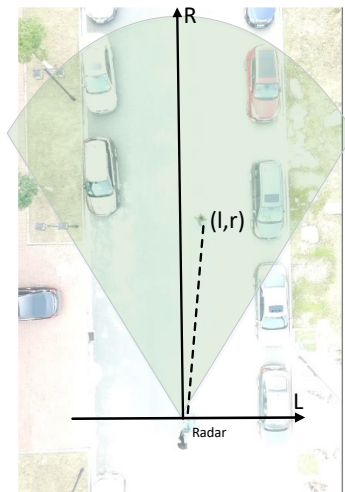


Figure 2. Radar coordinate system

The data collected by the system are filtered using  $\alpha$ - $\beta$  filter, ordinary Kalman filter and Sage-Husa adaptive Kalman filter. In order to verify that the Sage-Husa adaptive Kalman filter can get a good filtering effect in the scene with more interference, this article enumerates four experiments in different scenarios. The four scenarios include a road scene with less interference (Scenario 1), road scene with more interference (Scenario 2), tram scene with less interference (Scenario 3) and tram scene with more interference (Scenario 4), as shown in Figures 3-10. Among them, the blue dot line represents the true value of the target, the black dashed line represents the  $\alpha$ - $\beta$  filter, the magenta dashed line represents the classical Kalman filter, and the red solid line represents the adaptive Kalman filter.

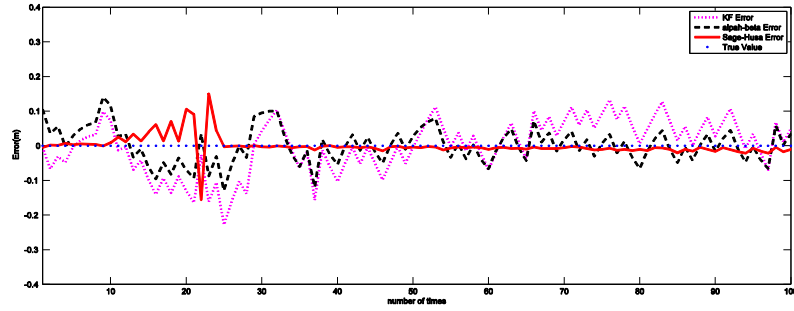


Figure 3. Scenario 1 target longitudinal distance filtering error

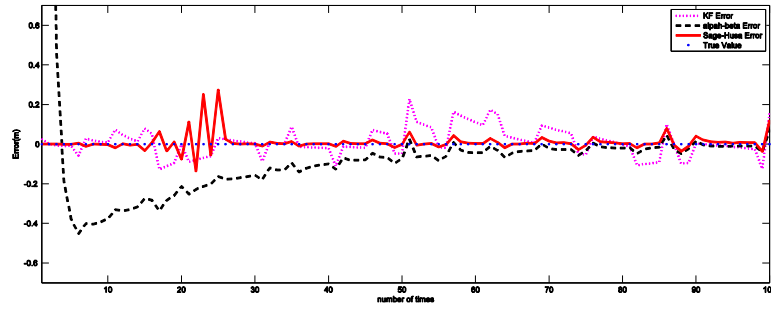


Figure 4. Scenario 1 target lateral distance filtering error

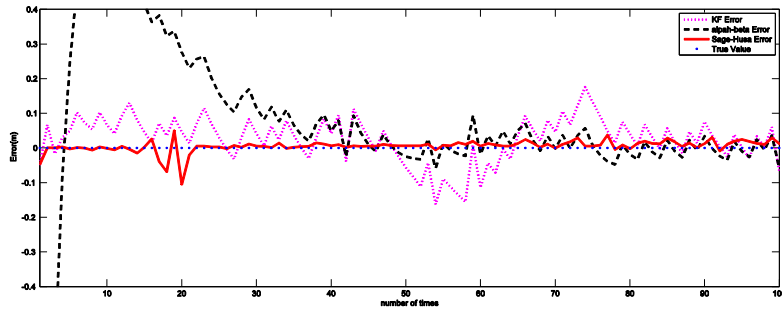


Figure 5. Scenario 2 target longitudinal distance filtering error

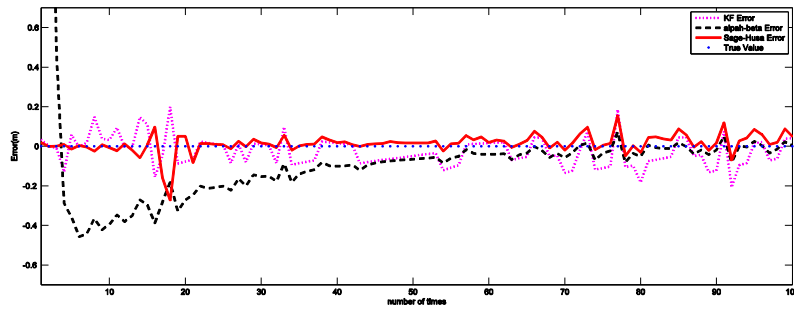


Figure 6. Scenario 2 target lateral distance filtering error

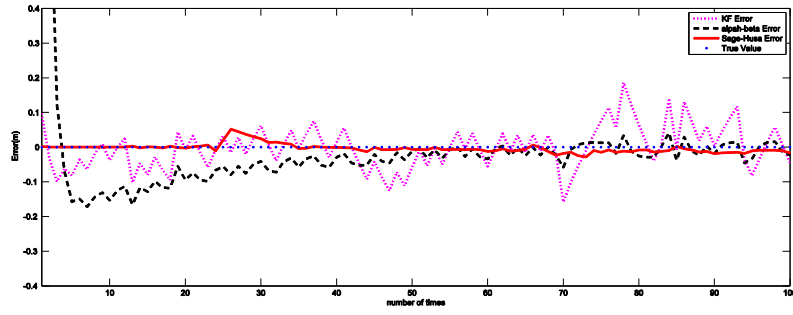


Figure 7. Scenario 3 target longitudinal distance filtering error

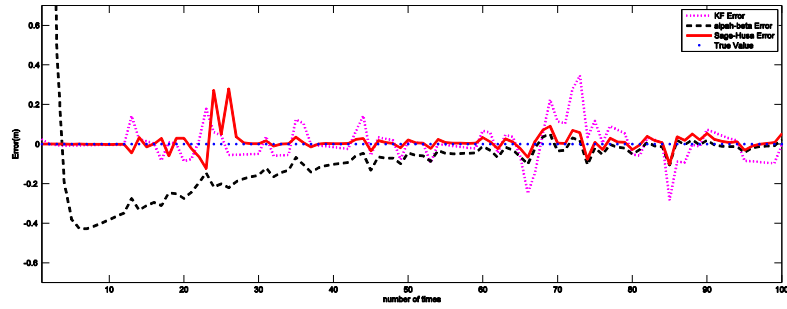


Figure 8. Scenario 3 target lateral distance filtering error

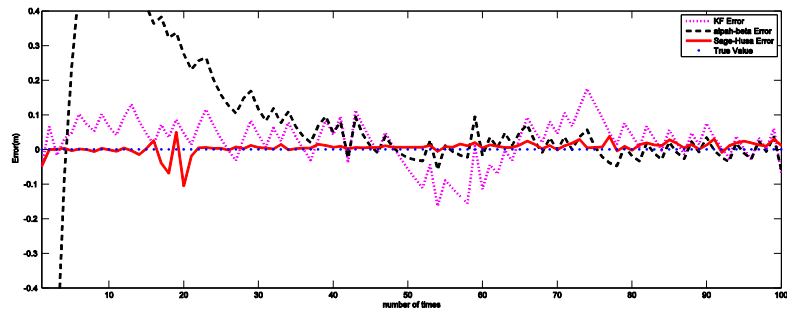


Figure 9. Scenario 4 target longitudinal distance filtering error

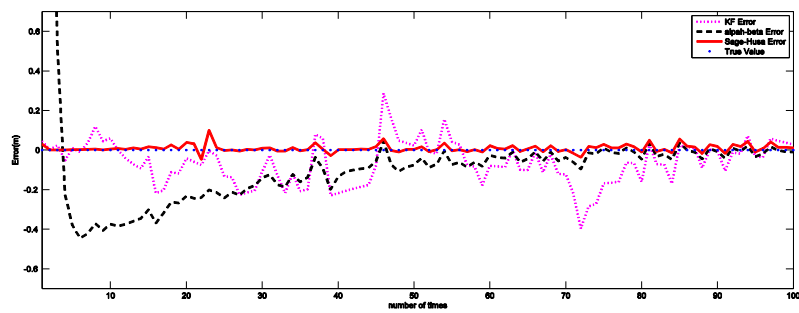


Figure 10. Scenario 4 target lateral distance filtering error

As can be seen from Figure 3-10, the accuracy and stability of the adaptive Kalman filter are significantly higher than the other two filters. The adaptive Kalman filtering can track the target well, even in the presence of interfering targets. In addition, the adaptive Kalman filter also converges faster than the other two filters. Therefore, the adaptive Kalman filter is more suitable for tracking radar targets.



#### 4.2. Comparison of target position before and after filtering

In order to intuitively verify the performance of adaptive Kalman filtering algorithm for radar target tracking, this paper also uses MMW radar and machine vision information fusion to detect targets (see Appendix for specific methods). This method can not only obtain the location information of the target, but also get the shape, texture and other characteristics of the target.

Figure 11-14 show the comparison of the results before and after filtering when the radar is affected by flicker noise at different times in different experimental scenarios. The red dot is the target position before filtering and the blue dot is the position information after filtering. From Figure 11-14, it can be seen that the target position after filtering is closer to the true position than before filtering.



Figure 11. Position comparison in road with less interference

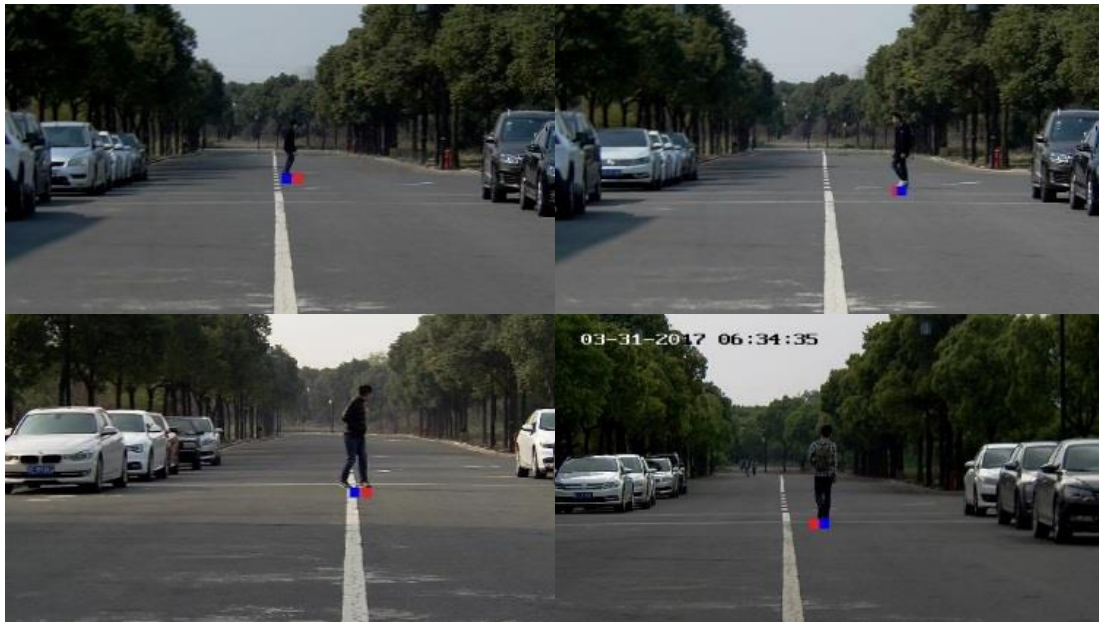


Figure 12. Position comparison in road with more interference



Figure 13. Position comparison in tram with less interference

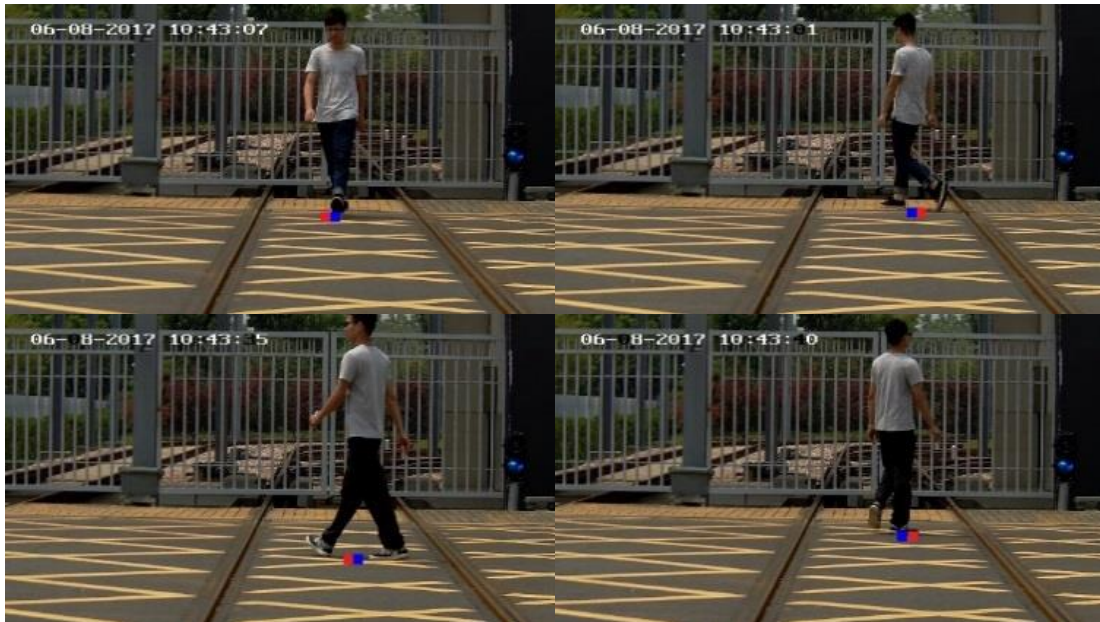


Figure 14. Position comparison in tram with more interference

#### 4.3. Estimation of lost target by filtering algorithms

Due to the limitation of MMW radar measurement principle and the influence of electromagnetic interference in the process of using it, the radar may also have a losing target situation. The main feature of this situation is that the radar will only lose a target in a frame or a few consecutive frames, and will continue to detect the target in subsequent detection. Figure 15 shows the experimental data when the radar lost the target, and then it makes up for the lost target information by adaptive Kalman filter algorithm. The blue point line is the true value of the target, the black dotted line is the measured value, and the red line is the filter value. The data in the green frame is the data when the radar loses the target. At this time there is no measurement value, only the true value and the estimated value.

It can be easily seen from Figures 15-16 that the location information of the lost target obtained by adaptive Kalman filtering is close to the true value, and can be used as an approximate value of the true value.

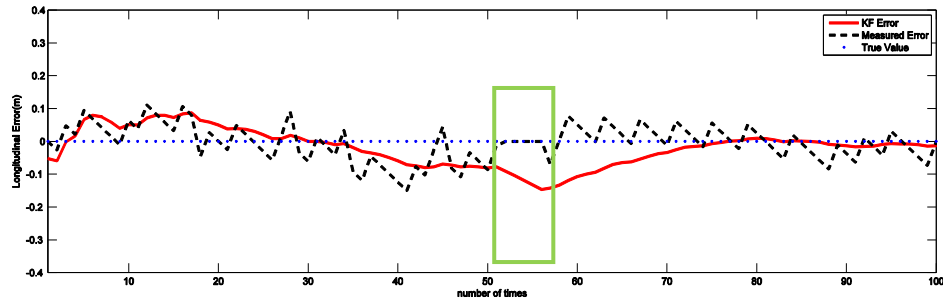


Figure 15. Longitudinal distance estimation when losing target

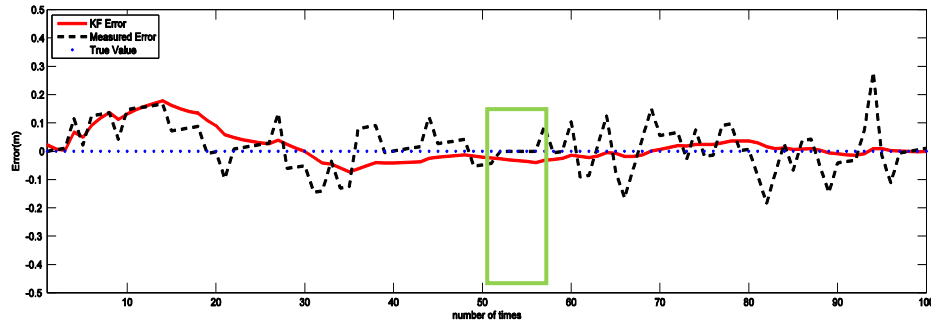


Figure 16. Lateral distance estimation when losing target

In order to further verify the accuracy of the target information complemented by the filtering algorithm, we select a series data of radar losing target from a large number of experimental data. Then, we compare the information complemented by different filtering algorithms with the real information of the target, as shown in Table 1.

Table 1. 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

From Table 1, it can be seen that the adaptive Kalman filter algorithm has higher accuracy than the ordinary Kalman filter. The target information complemented by adaptive Kalman filter is closer to the real value. Therefore, when the radar loses target, the adaptive Kalman filter can be used to approximate the true value of the target.

## 5. Conclusions

A MMW radar target tracking algorithm based on Sage-Husa adaptive Kalman filter is proposed in this paper. Firstly, the filtering algorithm is designed for road target models, which improves the precision of the radar. Then, the fusion of radar and machine vision information is used to directly reflect the effect of target tracking. Finally, the accuracy of the target information estimated by the algorithm is verified in view of the possible loss of target in the millimeter wave radar. The experimental results show that this method can accurately track radar target and solve the problem of radar target loss. In summary, the proposed method improves the accuracy and reliability of millimeter wave radar and contributes to the millimeter wave radar to play a more adequate role in intelligent driving safety assistance system.

## Acknowledgements

This work was partly financially supported by the fund projects of the Jiangsu Provincial Department of Science and Technology (BY2015039-12). The authors thank the anonymous reviewers.

## References

1. R. H. Abiyev, M. Arslan, and I. Gunsul, et al., "Robot Pathfinding Using Vision Based Obstacle Detection," *IEEE International Conference on Cybernetics. IEEE*, 2017:1-6 --1
2. M. Caris, S. Stanko, and W. Johannes, et al., "Detection and Tracking of Micro Aerial Vehicles with Millimeter Wave Radar," *Radar Conference. IEEE*, 2017:1553-1555 ---5
3. Gang Chen, Wei Wang, and Peng Di, "Dynamic Positioning Optimization Based on Kalman Filtering," *Ship Electronic Engineering*, 2016, 36 (5): 60-62 ---14
4. L. Farhi, L. Zhao, and Z. Liao, "Constrained Weighted Least Square Optimization for Vehicle Position Tracking," *Global Telecommunications Conference*, 2009. GLOBECOM. IEEE, 2009:1-6 ---12
5. Zhenhai Gao, Jun Wang, and Jing Tong, et al., "Estimation of Motion State of Vehicle Mounted Millimeter Wave Radar for Front Target," *Journal of Jilin University (Engineering Edition)*, 2014, 6:001 ---6
6. Liwen He, Yanpeng Li, and Bo Fan, "An Improved  $\alpha$ - $\beta$  Filter Algorithm," *Modern Electronic Technique*, 2012, 35 (21): 28-30 --11
7. R.E. KALMAN, "A New Approach to Linear Filtering and Prediction Problem," *Transactions of the ASME-Journal of Basic Engineering*, 1960, 82(Series D):35-45 ---8
8. Pengfei Li, Jianping Yu, and Liangqun Li, "Maneuvering Target Tracking based on Fuzzy Adaptive  $\alpha$ - $\beta$  Filtering," *System Engineering and Electronic Technology*, 2008, (11): 2138-214 ---10
9. A. Macaveiu, and A. Campeanu, "Automotive Radar Target Tracking by Kalman Filtering," *International Conference on Telecommunication in Modern Satellite, Cable and Broadcasting Services*, IEEE, 2014:553-55 ---16
10. B. Mustapha, A. Zayegh, and R. K. Begg, "Reliable Wireless Obstacle Detection System for Elderly and Visually Impaired People with Multiple Alarm Units," *Computer Communications and Control Technology (I4CT) 2014 International Conference on*, pp. 271-276 ---3
11. Bo Pan, Jinfu Feng, and Qian Li, et al., "Millimeter Wave / Infrared Multisensor Fusion Tracking Algorithm," *Infrared and Millimeter Wave Journal*, 2010, 29 (3): 230 ---17
12. Cheng Pang, "Front Vehicle Detection System Based on Data Fusion of Range Radar and Machine Vision." *Southeast University*, 2015 ---7
13. Zhizhuan Peng. Research on information fusion algorithms for MMW Radar/IR composite guidance. *Air Force Engineering University*, 2007 ---18
14. Peter Rohal, and Jan Ochodnický, et al., "Radar Target Tracking by Kalman and Particle Filter," *Communication and Information Technologies (KIT). IEEE*, 2017:1-4 ---15
15. A. P. Sage, and G. W. Husa, "Adaptive Filtering with Unknown Prior Statistics," *Joint Automatic Control Conference*. 1969(7) : 760-769 ---9
16. A. Scheel, S. Reuter, and K. Dietmayer, "Vehicle Tracking Using Extended Object Methods: An Approach for Fusing Radar and Laser," *IEEE International Conference on Robotics and Automation*. IEEE, 2017:231-238 ---4
17. Zheng Tang, Ming Hao, and Jiyuan Pan, et al., "Kalman Filter Weighted Covariance Fusion Tracking Algorithm Based on," *Modern Navigation*, 2013, 4 (02): 148-152 ---13
18. G. G. Volodymyr, and M. V. Dmytro, "Detection of Radar Targets Moving with Acceleration. Microwaves," *Radar and Remote Sensing Symposium (MRRS). IEEE*, 2017: 125 – 130 --2

**Guangyao Zhai**, male, graduate student of the School of Rail transportation, Soochow University. Main research directions include millimeter wave radar, machine vision and information fusion.

**Cheng Wu**, male, Suzhou, Jiangsu. He graduated from the computer engineering major of Northeastern University and received his doctorate. He is now an associate professor of Soochow University. The main research directions include computer engineering, artificial intelligence, image processing and so on.

**Yiming Wang**, female, Suzhou, Jiangsu. She is a professor and doctoral tutor of Soochow University. She is also a senior member of China Electronics Society, a member of IEEE, and a leader of communication and information system in Soochow University. The current research interests are wireless communication network, cognitive radio, ultra-wideband communication and so on.

## Appendix

The space fusion of millimeter wave radar and camera can realize the unification of millimeter wave radar coordinate system, camera coordinate system, 3D world coordinate system and image coordinate system. Thus, the target position acquired by radar is converted to the image acquired by camera, and then the target region of interest is generated. Figure 1 depicts the position relations of millimeter wave radar coordinate system, camera coordinate system, 3D world coordinate system and image coordinate system. As shown in Figure 1, the camera coordinate system is  $O_c - X_c Y_c Z_c$ , which takes the camera optical



center as the origin. The  $X_c$  axis points to the ground. The  $Y_c$  axis points to the right side of the vehicle and the  $Z_c$  axis points to the direction of the vehicle. The radar coordinate system is  $O_r - X_r Y_r Z_r$ , which takes the radar geometric center as the origin. The  $X_r$  axis points to the left of the radar. The  $Y_r$  axis points vertically upwards and the  $Z_r$  axis points to the direction of the vehicle. The 3D world coordinate system is  $O_w - X_w Y_w Z_w$ . The image coordinate system is  $O_p - X_p Y_p$ , which is a two-dimensional coordinate system.

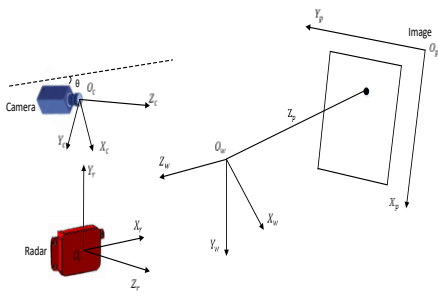


Figure A.1. Coordinate systems

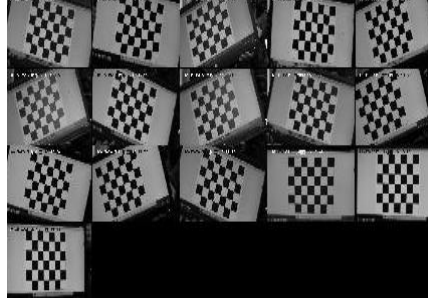


Figure A.2. Camera calibration checkerboard



Figure A.3. Spatial fusion

The coordinate relation between radar coordinate system and 3D world coordinate system is shown in Equation (1).

$$\begin{cases} X_w = H \\ Y_w = X_r + l \\ Z_w = -Z_r + L \end{cases} \quad (1)$$

Among them,  $H$  is the height of the world coordinate system origin from the ground.  $l$  and  $L$  are the offset of  $O_w$  and  $O_r$  in the  $X_r$  direction and  $Z_r$  direction, respectively. The relationship between the world coordinate system and the image coordinate system is obtained by the position relation of each coordinate system, as shown in Equation (2).

$$Z_c \begin{bmatrix} X_p \\ Y_p \\ 1 \end{bmatrix} = \begin{bmatrix} 1/d_x & 0 & X_{p0} \\ 0 & 1/d_y & Y_{p0} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R & t \\ 0^T & 1 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \quad (2)$$

Among them,  $(X_p, Y_p)$  is the coordinate of the projection points in the image coordinate system.  $d_x$  and  $d_y$  are the physical dimensions of each pixel in the X axis and the Y axis, respectively.  $(X_{p0}, Y_{p0})$  is the camera's main point offset.  $f$  is the focal length of the camera.  $R$  is the rotation matrix, which is a  $3 \times 3$  orthogonal unit matrix.  $t$  is the translation vector. In the above parameters,  $(d_x, d_y)$ ,  $(X_{p0}, Y_{p0})$  and  $f$  are the camera internal parameters, while  $R$  and  $t$  are the camera external parameters. They can be obtained by camera calibration. In the camera calibration, the Zhang Zhengyou calibration method has good robustness and strong practicability. The method realizes the camera calibration by collecting a plurality of different viewpoints from the two-dimensional target image. This paper first collects the standard checkerboard images in different positions and angles, and then calculates the internal and external parameters of the camera through Zhang Zhengyou calibration method. Figure 2 shows the camera calibration checkerboard.

The radar coordinates of the target can be converted into image coordinates by substituting the acquired camera parameters into Equation (1) and Equation (2). As shown in Figure 3, the red dot is the position of the radar target being converted to the image. Thus, the spatial fusion between radar and camera is realized.