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An Improved Kalman Filtering Algorithm for Maneuvering Target Tracking Based on ANFIS

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Abstract: Kalman filtering is widely used in maneuvering target tracking. However, conventional Kalman filtering always fails to track the maneuvering target when there is a sudden change in the target motion state. In this paper, an improved Kalman filtering algorithm which based on the adaptive neural fuzzy inference system (ANFIS) is proposed. The improved algorithm can update the measurement noise covariance in real-time by ANFIS through observing the covariance matrix of Kalman residual. In this way, the tracking error can be reduced. Then, the comparison and analysis of the experiment results between the original Kalman filtering algorithm and the improved one have been carried out. The experiment results show that the tracking error is obviously reduced and the accuracy is significantly boosted after the original Kalman filtering algorithm was substituted by the improved one. To explore the influence of ANFIS parameters on the tracking error, the setting rules of them were analyzed at the end of this paper. *Copyright © 2013 IFSA.*

Keywords: Kalman filter, Maneuvering target tracking, Adaptive Neuro-Fuzzy Inference System, Covariance matrix, Parameter setting rules.

1. Introduction

Kalman filtering algorithm was put forward in literature [1] by Kalman, a Hungarian-American mathematician, in 1960, and it was promoted to continuous system together with R. S. Bucy in 1961 [2]. As a linear autoregressive filter, it is not only very common in engineering applications, but also has a good performance in moving target tracking. Kalman filtering algorithm is an ideal estimation algorithm when it is used for non-motor vehicle target tracking. But when the target is in the maneuvering motion, the tracking model will not be consistent with the actual motion model and the target state estimation will deviate from the true status, thus Kalman filter will diverge and filtering performance will drop rapidly. In view of the problems the Kalman filter have in maneuvering target tracking, scholars have put forward various improved methods, such as Extend Kalman Filter (EKF), Federal Kalman Filter, and Adaptive Kalman Filter, etc. However, it is a precondition that EKF must follow the assumption of Gaussian process, which is not always satisfied in the actual application systems [3]. Its disadvantages include parameter adjustment difficulty, poor robustness and high computing complexity. Moreover, the EKF is based on linearization of the system dynamics, which results in a suboptimal application of the recursive estimation of the standard Kalman Filter [4, 5]. So, it is not suitable to use on high mobility conditions.

To overcome those defects of the algorithms mentioned above, an improved algorithm, which is based on the original Kalman Filter and ANFIS, is

proposed to update the measurement noise covariance in target tracking system in this paper [6]. The Adaptive Neural Fuzzy Inference System (ANFIS) [7] is proposed by Jyh-Shing Roger Jang in 1993. It inherits the advantages of fuzzy logic and neural network. At the same time, ANFIS has discard not only the disadvantages of the fuzzy inference system, such as strong dependence on expert experience and poor self-learning ability, but also that of the neural network, such as lack of training samples and poor universality of its system architecture. Therefore, it can not only adjust its structure adaptively according to the operation environment of the system, but also obtain the membership function by blended learning rule.

The simulation results show that the improved algorithm has higher accuracy in maneuvering target tracking than the original one.

2. Principle and Defect of the Original Algorithm

The target status equation and measurement equation are defined as follows:

$$X(k) = \Phi X(k-1) + W(k-1) \tag{1}$$

$$Z(k) = HX(k) + V(k) \tag{2}$$

In the status equation (1), X is the state vector and Φ is a transition matrix of the system. In the measurement equation (2), Z is the measurement vector and H is the measurement matrix of the system. $W(k)$ and $V(k)$ are the zero-mean Gaussian noises, representing system noise and measurement noise respectively.

Kalman filtering algorithm consists of two steps named prediction and measurement update. Based on the linear system above, the prediction step is derived as follows:

$$\hat{X}(k \mid k-1) = \Phi \hat{X}(k-1 \mid k-1) \tag{3}$$

$$P(k \mid k-1) = \Phi P(k-1 \mid k-1)\Phi^{\mathrm{T}} + Q(k-1) \tag{4}$$

In formula (3), $\hat{X}(k \mid k-1)$ is the state vector prediction, $\hat{X}(k \mid k-1)$ is the state vector estimation of $X(k-1)$ at time instant $k-1$. Formula (4) is an error covariance matrix of the prediction state, where $P(k-1 \mid k-1)$ is the error covariance matrix of $X(k-1)$ at time instant $k-1$. $Q(k)$ is the covariance of $W(k)$.

The measurement update step is carried out by the following equations:

$$\tilde{Z}(k) = Z(k) - \mathrm{H}\hat{X}(k \mid k-1) \tag{5}$$

$$S(k) = HP(k \mid k-1)H^{\mathrm{T}} + R(k) \tag{6}$$

$$K(k) = P(k \mid k-1)H^{\mathrm{T}} S^{-1}(k) \tag{7}$$

$$\hat{X}(k \mid k) = \hat{X}(k \mid k-1) + K(k)\tilde{Z}(k) \tag{8}$$

$$P(k) = \left(I - K(k)H\right)P(k \mid k-1) \tag{9}$$

Kalman residual is denoted as $\tilde{Z}(k)$ and described as formula (5). The theoretical covariance matrix of $\tilde{Z}(k)$ is showed as formula (6). $R(k)$ is the covariance of $V(k)$. In addition, Kalman gain $K(k)$ is depicted in formula (7). $\hat{X}(k \mid k)$ is the state estimation and $P(k)$ is the estimation error covariance matrix. Compared with the theoretical covariance matrix $S(k)$ of Kalman residual the observed value $\hat{C}_{\tilde{z}}(k)$ can be obtained by the following formulas:

$$E\left[\tilde{Z}(k+1)\right] = \bar{\tilde{Z}}(k+1) \tag{10}$$

$$E\left[\left(\tilde{Z}(j+1) - \bar{\tilde{Z}}(j+1)\right)\left(\tilde{Z}(k+1) - \bar{\tilde{Z}}(k+1)\right)^{T}\right] = \begin{cases} C_{\tilde{z}}(k+1) & ,k = j \\ 0 & ,k \neq j \end{cases} \tag{11}$$

It can be known from formula (6) and (11) that there are differences between the observed covariance matrix $\hat{C}_{\tilde{z}}(k)$ and the theoretical value $S(k)$ of Kalman residual. When the target moves at a constant speed, the mean value of Kalman residual $\tilde{Z}(k)$ is zero. However, this value will change when the target have accelerations. Then, the observed covariance matrix $\hat{C}_{\tilde{z}}(k)$ of Kalman residual will not be consistent with the theoretical one [8]. In addition, it is inferred that the theoretical covariance matrix of $\tilde{Z}(k)$ is affected by the value of measurement noise covariance $R(k)$ as indicated in formula (6). In order to remedy the flaws of the original method mentioned above, the improved algorithm, which is based on ANFIS, is put forward to enhance tracking accuracy. It can update the measurement noise covariance matrix $R(k)$ in real-time, then keep the observed value of the Kalman residual covariance consistent with the theoretical one, and finally, make the target tracking experiment getting a better result.

3. The Improved Algorithm

3.1. Principle of the Improved Algorithm

From the analysis of original algorithm we can know that the target maneuvering will cause the observed covariance $\hat{C}_{\tilde{z}}(k)$ inconformity with the

theoretical value $S(k)$ of the Kalman residual, the tracking accuracy will decline rapidly and Kalman filter will diverge. Formula (6) shows the measurement noise covariance $R(k)$ can influence theoretical one, then the filtering effect will be affected also. So updating the measurement noise covariance can keep the observed covariance of the Kalman residual consistent with the theoretical one, and the tracking accuracy will be improved finally. Therefore, an improved Kalman filtering algorithm, in which the measurement noise covariance is updated in real-time by ANFIS, is proposed. The flow chart is showed as Fig. 1.

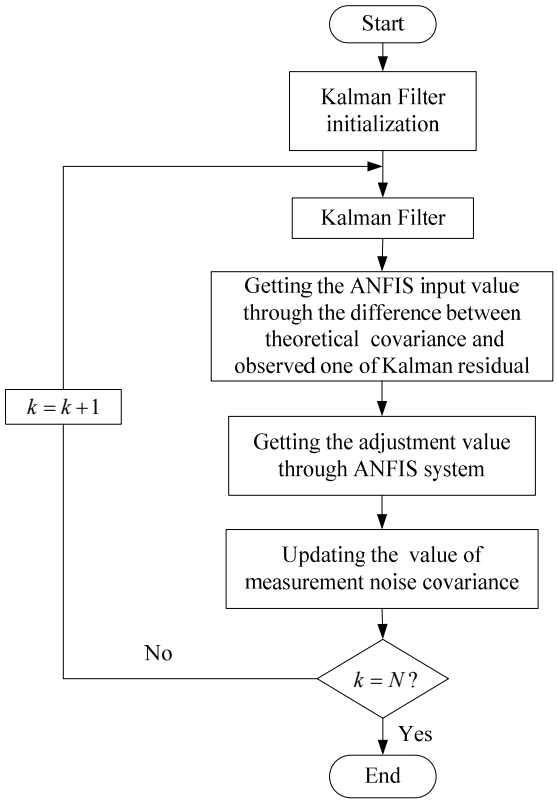


Fig. 1. Flow chart of the improved algorithm.

In the improved algorithm, the theoretical covariance of Kalman residual is defined as:

$$S(k) = HP(k \mid k-1)H^{\mathrm{T}} + \hat{R}(k), \qquad (12)$$

where $\hat{R}(k)$ takes the place of measurement noise covariance signed $R(k)$ in the original algorithm. The symbol $\hat{R}(k)$ is an estimate value of $R(k)$, which is updated by ANFIS in real-time.

3.2. Design of ANFIS System

It can be known that the observed covariance disagrees with the theoretical value of the Kalman residual when the speed of the moving target changes in the original algorithm. In order to overcome the defect, the improved algorithm updates the measurement noise covariance in real-time based on $D(k)$ by ANFIS to ensure that the two values of the Kalman residual covariance are consistent with each other.

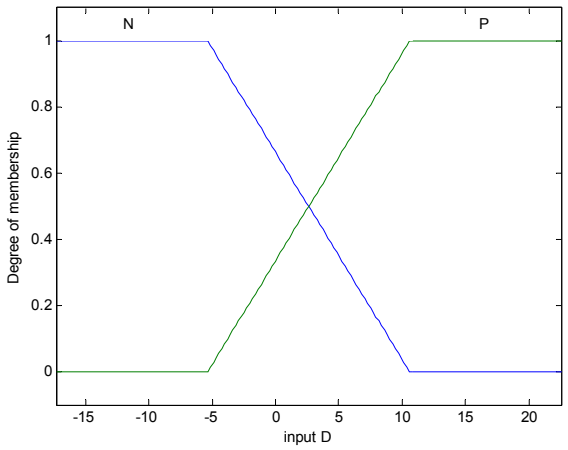
The variable $D(k)$ is defined as:

$$D(k) = S(k) - \hat{C}_{\tilde{z}}(k) \qquad (13)$$

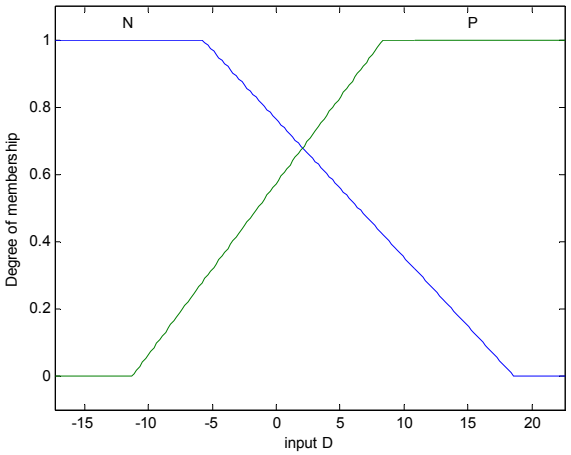
Measurement noise covariance can be updated as follows:

$$\hat{R}(k) = R(k) + \Delta R(k) \qquad (14)$$

The input value is mapped into fuzzy sets in the universe of discourse. They are labeled as: N = Negative, P = Positive. In this paper, the trapezoidal shaped function has been chosen as the membership function (MF) to characterize fuzzy sets. The initial and final membership functions of the input parameter are showed as Fig. 2.



(a) Initial membership function



(b) Final membership function

Fig. 2. The initial and final generalized bell shaped membership function of ANFIS.

According to formulas (6), (11) and (13), the value of $D(k)$ is calculated. The value of $\Delta R(k)$ is get by expert experience. In this way, a set of $D(k)$ and $\Delta R(k)$ are obtained and used as input and output parameters respectively for ANFIS training. The input-output curve of ANFIS obtained from the ANFIS training is showed in Fig. 3.

The parameters of ANFIS are showed as Table 1.

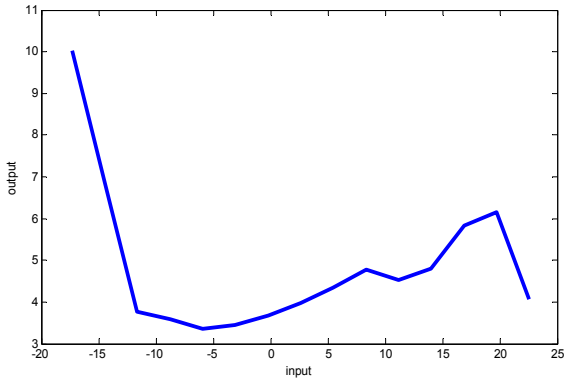


Fig. 3. Input-output relation curve of ANFIS.

Table 1. ANFIS parameters.

Parameters Name.	Value
Type of input MF	Trap
Type of output MF	Linear
Number of input MF	2
Number of Epoch	2000
Learning method	Hybrid
Number of training data pairs	110
Training error	3.5954

4. Experiments Comparison of the Improved Algorithm and Original One

The proposed algorithm is evaluated using different types of trajectories, including maneuvering and non-maneuvering trajectories. The results of the experiments have been compared with the original algorithm.

4.1. The Experiment of Non-Maneuvering Target Tracking

In this simulation, the initial position of the target is $(x, y) = (1000m, 1000m)$. The target moves with a constant velocity of $(v_x, v_y) = (10m/s, 10m/s)$ until the end of simulation at time T=150 s. The sample time is T=1 s and the covariance matrix of measurement noise $V(k)$ is $R(k) = diag(10,10)$. Fig. 4 shows the position error and velocity error of the two algorithms.

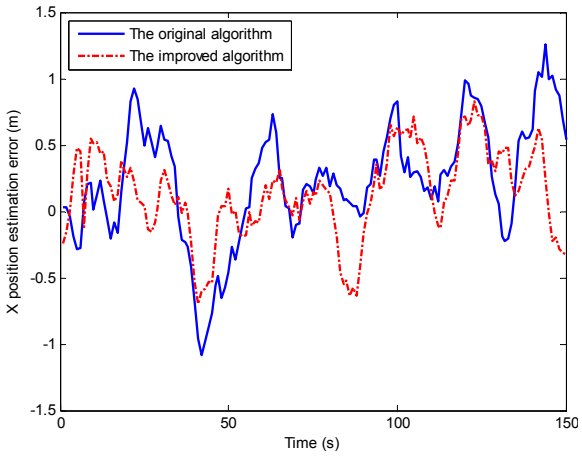


Fig. 4 (a). Tracking error comparisons for the non-maneuvering target – position error comparison on Axis-X.

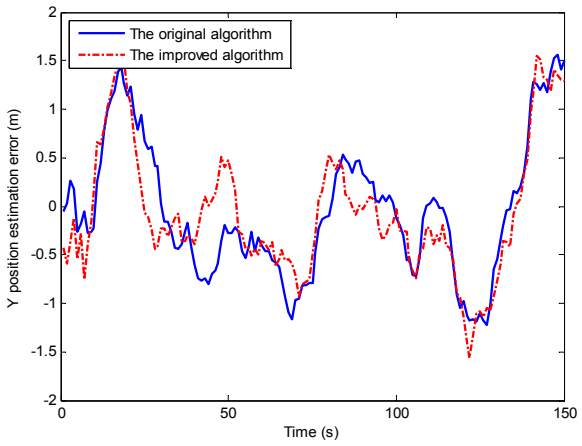


Fig. 4 (b). Tracking error comparisons for the non- maneuvering target – position error comparison on Axis-Y.

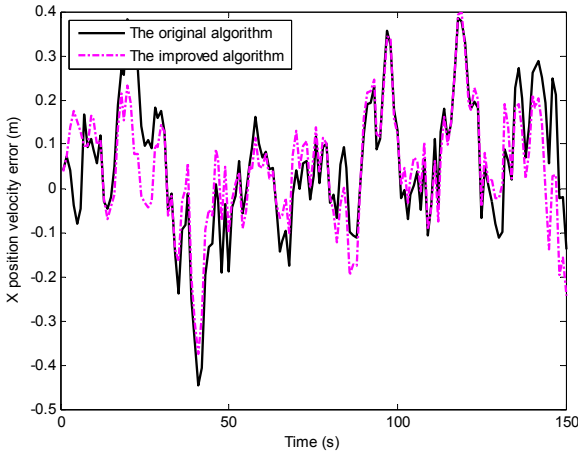


Fig. 4 (c). Tracking error comparisons for the non- maneuvering target – Velocity error comparison on Axis-X.

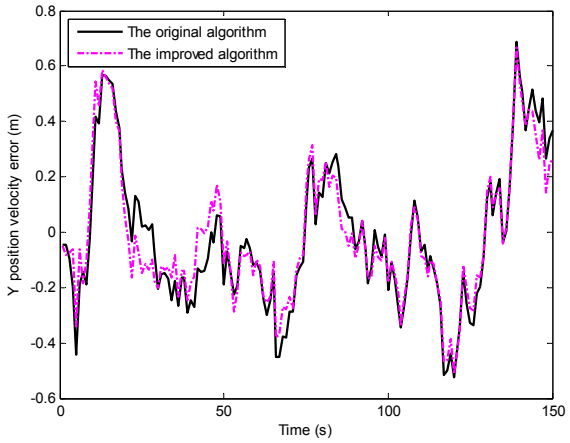


Fig. 4 (d). Tracking error comparisons for the non- maneuvering target – Velocity error comparison on Axis-Y.

The simulation result shows that the position error and velocity error of the two algorithms are both small and there are little difference of tracking accuracy between the two algorithms. So we can draw a conclusion that both the improved algorithm and the original one have a high tracking precision when the target movement is under the condition of non-maneuvering.

4.2. The Experiment of Maneuvering Target Tracking

It has a higher value for maneuvering target tracking. Fig. 5 is trajectory of the target for tracking.

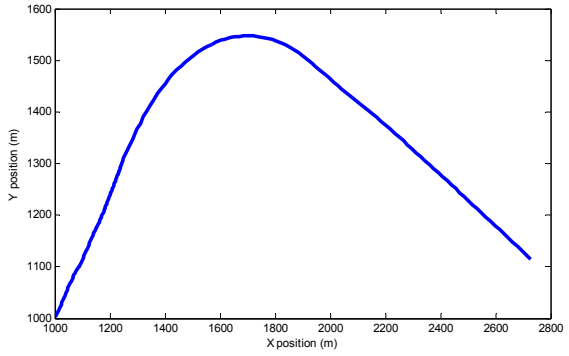


Fig. 5. Tracking trajectory.

The initial position of the target is $(x, y) = (1000m, 1000m)$. Target moves with the constant velocity of $(v_x, v_y) = (3m/s, 3m/s)$ until T=100 s. Then, an acceleration $(a_x, a_y) = (1m/s^2, 1m/s^2)$ is attached to the target, this acceleration continues until T=110 s. Next, the target turning with an angular velocity of $-\pi/100\,rad$ until T=150 s. Finally, the target moves with the constant velocity up to the end of simulation at time T=200 s. The sample time is T=1 s and the covariance matrix of measurement noise $V(k)$ is $R(k) = diag(10,10)$. Fig. 6 is the result of target tracking error. In Fig. 6, the experiment errors of the improved Kalman filtering algorithm and the original one are compared.

After 50 independent Monte Carlo runs, the means of estimation errors in target positions and velocities are shown in Fig. 6 respectively. It shows that the tracking error of the original algorithm becomes larger observably as the target movement changes. After the improved algorithm is used to replace the original one, the tracking error has been reduced effectively. The reason is that the measurement noise covariance is adjusted by ANFIS in the new algorithm, and the observed covariance of the Kalman residual keep consistent with the theoretical one. So the loss of the moving target can be prevented owe to the improved algorithm.

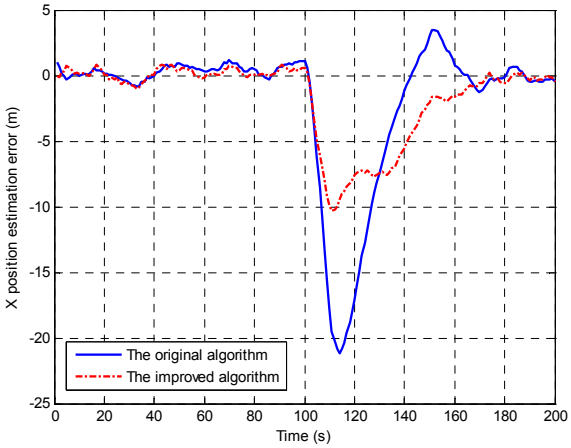


Fig. 6 (a). Tracking error comparisons for the maneuvering target – position error comparison on Axis-X.

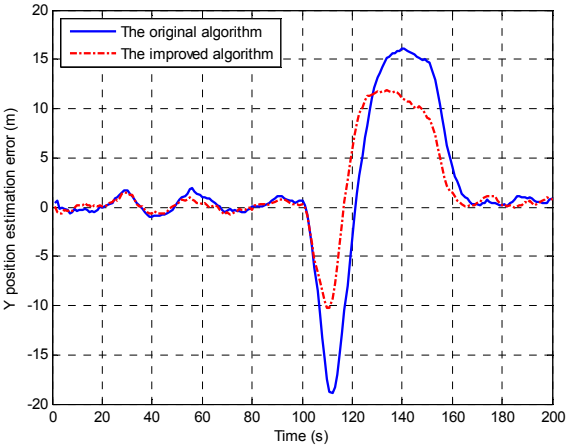


Fig. 6 (b). Tracking error comparisons for the maneuvering target – position error comparison on Axis-Y.

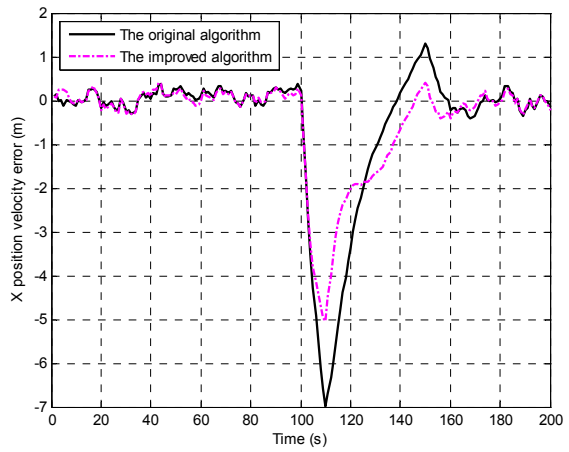


Fig. 6 (c). Tracking error comparisons for the maneuvering target – velocity error comparison on Axis-X.

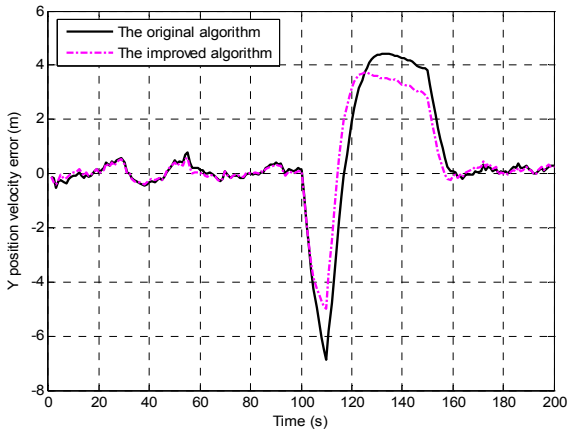


Fig. 6 (d). Tracking error comparisons for the maneuvering target – velocity error comparison on Axis-Y.

4.3. Experiment Error Analysis

Under the condition of maneuvering movement, the tracking RMSE from the time 101 s to 120 s and 151 s to 160 s are given in Table 2. It shows that the error in the improved algorithm has fallen by halfcompared to that in the original algorithm. The reason for tracking accuracy improvement is that the measurement noise covariance is compensated in real-time, and the theoretical covariance of Kalman residual is corrected after the ANFIS is used in the improved algorithm.

5. Parameter Setting Rules in the Improved Algorithm

5.1. How to Select the MF Type

Eight types of MF including "trimf", "trapmf", "gbellmf", "gaussmf", "gauss2mf", "pimf", "dsigmf" and "psigmf". Fig. 7 is mean error chart of different MF types under the condition of maneuvering. It can be seen that different MF have a certain influence on the result of the experiment. The trapezoidal membership function is used in proposed algorithm.

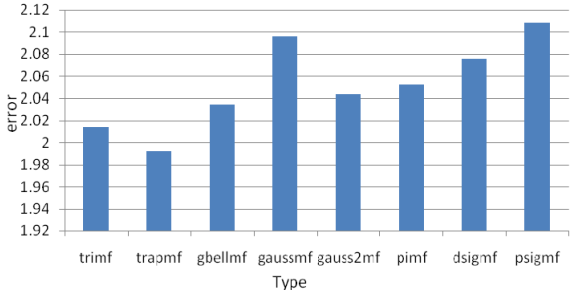


Fig. 7 (a). Mean tracking error comparison for different MFs – position error comparison on Axis-X.

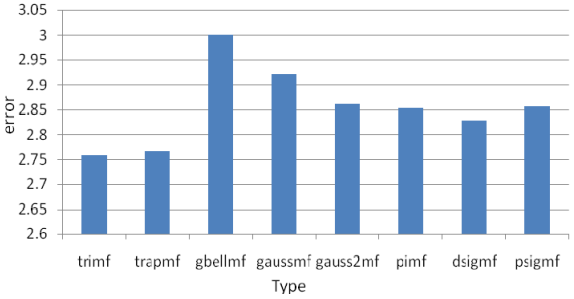


Fig. 7 (b). Mean tracking error comparison for different MFs – position error comparison on Axis-Y.

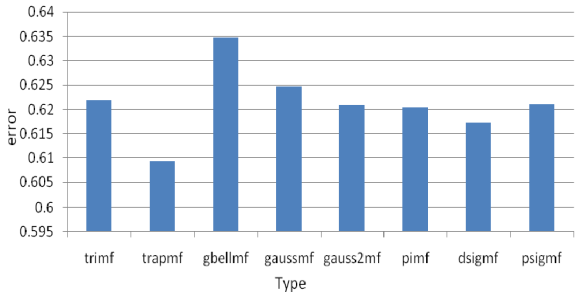


Fig. 7 (c). Mean tracking error comparison for different MFs – velocity error comparison on Axis-X.

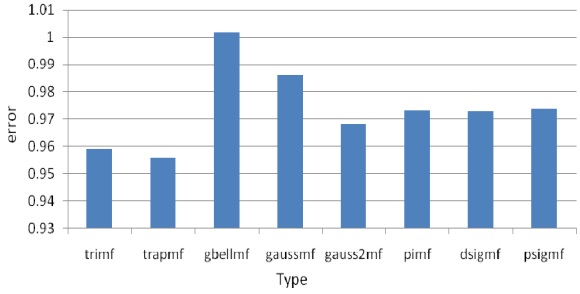


Fig. 7 (d). Mean tracking error comparison for different MFs – velocity error comparison on Axis-Y.

Table 2. Experiment error of the two algorithms.

Time (s)	Axis-X position error before improved (a)	Axis-X position error after improved (b)	b/a	Axis-Y position error before improved (c)	Axis-Y position error after improved (d)	d/c
101	0.787715	0.625835	0.794494	1.686792	1.596387	0.946404
102	2.606054	1.823011	0.699529	3.548462	2.665562	0.751188
103	4.749321	3.000903	0.631859	5.617258	3.752863	0.668095
104	6.866502	4.482359	0.652786	7.641443	5.060672	0.662267
105	9.190353	5.875119	0.63927	9.843422	6.158365	0.625633
106	11.48224	7.006653	0.610217	11.98458	6.982226	0.582601
107	13.66287	7.852465	0.57473	14.01386	7.772933	0.55466
108	15.74534	8.776145	0.557381	15.94145	8.315674	0.521639
109	17.64906	9.336604	0.529014	17.66089	8.802579	0.498422
110	19.23531	9.631069	0.500697	18.59588	8.536478	0.459052
111	20.27651	9.267071	0.457035	18.6146	7.321815	0.393337
112	20.84756	8.678934	0.416305	17.80919	5.640773	0.316734
113	20.77098	8.356742	0.402328	16.24923	3.852906	0.237113
114	20.52346	8.029615	0.391241	14.38829	1.912243	0.132903
115	19.93537	7.67606	0.385047	12.16674	0.007241	0.000595
116	19.24103	7.230875	0.375805	9.788791	1.773374	0.181164
117	18.30001	6.910295	0.377612	7.469768	3.197487	0.428057
118	17.47572	6.936306	0.396911	4.959671	4.526598	0.912681
119	16.50772	6.867078	0.415992	2.470856	5.986895	2.423005
120	15.38225	6.978077	0.453645	0.056858	7.139902	125.5747
151	3.157287	1.463629	0.463572	13.76305	6.830149	0.496267
152	3.108041	1.36227	0.438305	12.76665	6.373049	0.499195
153	3.146241	1.538614	0.489032	11.85909	5.510386	0.464655
154	2.911284	1.632569	0.560773	10.96797	4.831285	0.44049
155	2.669254	1.59024	0.595762	9.958173	4.07015	0.408725
156	2.416992	1.341616	0.555077	8.845108	3.361939	0.38009
157	2.073722	1.400649	0.675428	7.592983	2.853747	0.37584
158	1.647263	1.187787	0.721067	6.336806	2.249836	0.355043
159	1.471813	0.898155	0.610238	5.248879	1.75651	0.334645
160	1.299635	0.750826	0.577721	4.269877	1.541745	0.361075
Average	10.50456	4.950252	0.471248	10.07055	4.679392	0.464661

5.2. How to Select the MF Number

In the experiment below, the membership function is set as trapezoidal. The motion of the target is maneuvering. Fig. 8 is the mean error chart when the number of membership functions is set as 2, 3, 4, 5, 6 respectively. It can be seen that the mean tracking error increases evidently with the increase of the membership function number. Therefore, the membership function number of the improved algorithm is adopted as 2, under the condition of which the mean tracking error is least.

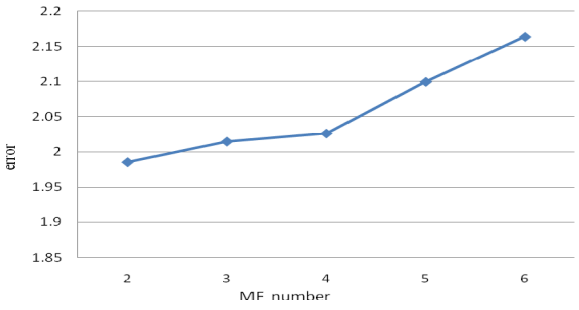


Fig. 8 (a). Mean tracking error comparison for different MF number – position error comparison on Axis-X.

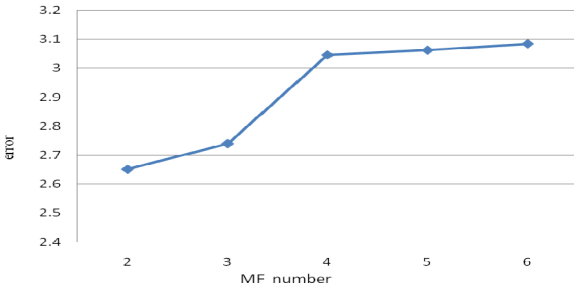


Fig. 8 (b). Mean tracking error comparison for different MF number – position error comparison on Axis-Y.

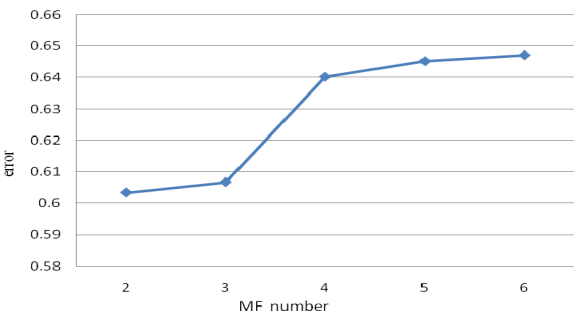


Fig. 8 (c). Mean tracking error comparison for different MF number – velocity error comparison on Axis-X.

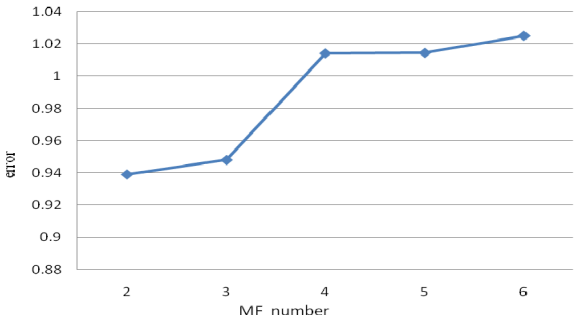


Fig. 8 (d). Mean tracking error comparison for different MF number – velocity error comparison on Axis-X.

6. Conclusions

After the principle of the original Kalman filtering algorithm for maneuvering target tracking and its defects are introduced, an improved Kalman filtering algorithm based on ANFIS is proposed in this paper. In the improved algorithm, the value of measurement noise covariance is updated in real time by ANFIS system and the theoretical value of the Kalman residual covariance is kept consistent with the observed one. Then, the simulation experiments are carried out and the tracking error are quantitatively analyzed. In addition, the parameter setting rules for ANFIS design are also put forward based on a serial of simulation experiments. The experiment results show that the accuracy of the maneuvering target tracking has been improved in the improved Kalman filtering algorithm comparing with the original one. However, the improved algorithm still has a flaw that the tracking accuracy of the improved algorithm will be influenced greatly by the training data of ANFIS. So it is a problem requiring further research in the future.

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