Study of maneuvering target tracking algorithm based on Kalman filter and ANFIS

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Abstract

Although Kalman filtering algorithm has been widely used in the maneuvering target tracking, conventional Kalman filtering algorithm always fails to track the maneuvering target as the target changes its movement state suddenly. In order to overcome its disadvantages, an improved Kalman filtering algorithm that based on the adaptive neural fuzzy inference system (ANFIS) is proposed in this paper. In the improved algorithm, the covariance matrix of Kalman residual is gainer and the measurement noise covariance can be updated in real-time by ANFIS module. Finally, the comparison and analysis of the experiment results between the original Kalman filtering algorithm and the improved one has 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.

Keywords: maneuvering Target tracking, Kalman filter, Adaptive Neuro-Fuzzy Inference System (ANFIS)

1 Introduction

Kalman filtering algorithm was put forward by Kalman in literature [1] in 1960, and it was promoted to continuous system together with R S Bucy in 1961 [2]. It is not only very common in engineering applications, but also has a good performance in moving target tracking. Kalman filtering algorithm plays a good role in the non-motor vehicle target tracking. However, when the target is in the maneuvering motion, the tracking model cannot keep pace with the actual motion model changes and the target state estimation will deviate from the true status, thus Kalman filter will diverge and the tracking accuracy will drop rapidly. In view of the defect of the original Kalman filtering algorithm, scholars have put forward various improved methods, such as Federal Kalman Filter, Extend Kalman Filter (EKF), and Adaptive Kalman Filter, etc., and among them EKF is used widely very much. However, a precondition of EKF is that it must follow the assumption of Gaussian process, which is not always satisfied in the actual application systems [3]. In the EKF, parameters cannot be adjusted easily. Further, more, poor robustness and high computing complexity are also its disadvantages. Because the EKF is usually used in the linear system, which results in a suboptimal application of the recursive estimation of the standard Kalman Filter [4, 5], tracking error will be too large to be used in the maneuvering target tracking.

The Adaptive Neural Fuzzy Inference System (ANFIS) [6] 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.

Because of the advantages of ANFIS, 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 [7]. The simulation results show that the improved algorithm has higher accuracy in maneuvering target tracking than the original one.

2 Analysis of the original Kalman filtering algorithm

2.1 DEFECT OF THE ORIGINAL ALGORITHM

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

$$X(k)\Phi X(k-1)+W(k-1) \quad (1)$$

$$Z(k)=HX(k)+V(k) \quad (2)$$

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

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:

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

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

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

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

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

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

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

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

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

Kalman residual is denoted as $\tilde{Z}(k)$ and described as formula (5). The theoretical covariance matrix of it is showed as formula (6). In addition, Kalman gain is depicted in formula (7). $\hat{X}(k|k)$ is a state estimation, $P(k)$ is an estimation error covariance matrix. Compared with the formula (6), the observed covariance matrix of Kalman residual $\hat{C}_2(k)$ can be obtained by the following formulas:

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

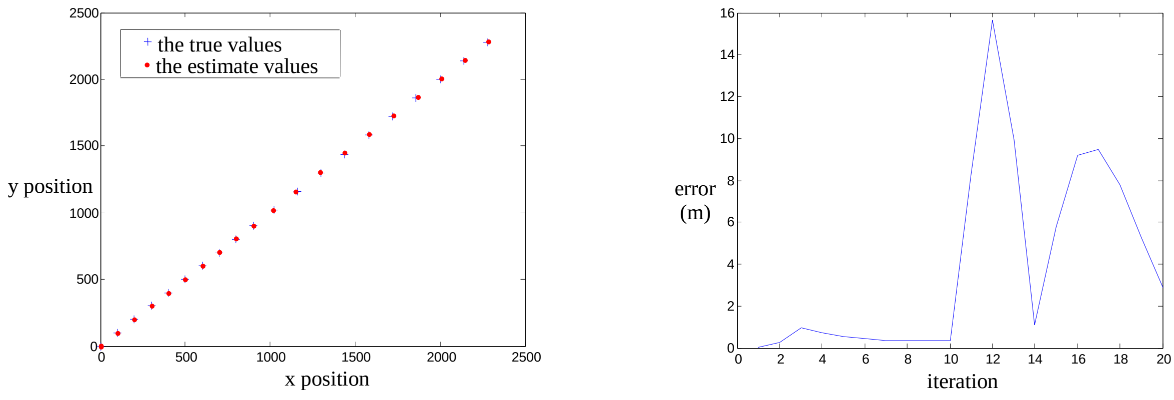
$$E = \left[\left(\tilde{Z}(j+1) - \tilde{\tilde{Z}}(j+1)\right)\left(\tilde{Z}(k+1) - \tilde{\tilde{Z}}(k+1)\right)^T\right] = \begin{cases} \hat{C}_2(k+1), & k = j \\ 0, & k \neq j \end{cases} \tag{11}$$

It is can be known from formula (6) and (11) that there are differences between the observed covariance matrix and the theoretical value of Kalman residual. When the target moves at a constant speed, the mean value of Kalman residual is zero. However, this value will change when the target have accelerations. Then, the observed covariance matrix of Kalman residual will not be consistent with the theoretical one [8]. In addition, it is inferred that the covariance matrix of $\tilde{Z}(k)$ is affected by the value of measurement noise covariance as indicated in formula (6). In order to remedy the flaws of the original method mentioned above, the improved algorithm is put forward to enhance tracking accuracy.

2.2 EXPERIMENT RESULT OF THE ORIGINAL ALGORITHM

In this paper, the original algorithm is applied to the simulation experiment of moving target tracking. Supposing that the initial position of the target is $(x, y) = (0m, 0m)$, the initial velocity is $(v_x, v_y) = (50m/s, 50m/s)$. The sample time is $T = 2s$. In the 10th sampling period $(t = 20s)$ an instantaneous acceleration $(a_x, a_y) = (10m/s, 10m/s)$ will be attached to the target, lasting $2s$. Tracking results are showed in Figure 1.

Figure1 (b) shows that when the target moves at a uniform speed, the tracking accuracy is high, but the tracking error increased instantly and the tracking effect reduced suddenly after the speed of the moving target has been changed. From the defects of the original algorithm analyzed in 2.1, it is known that as the speed of the moving target changes, the mean value of the Kalman residual will change correspondingly. Moreover, it will cause the difference between the observed covariance matrix of the Kalman residual and the theoretical one, which will increase the filtering error. This is the main reason of Kalman filter performance drop rapidly. This paper presents a new method that based on ANFIS to improve the original Kalman filtering algorithm. The improved algorithm can update the measurement noise covariance matrix 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.



a) b)

FIGURE 1 Experiment results of the original Kalman filtering algorithm in target tracking: a) Tracking displacement, b) Tracking error.

3 The improvement of Kalman filtering algorithm

To overcome the limitation that the original algorithm, an improved IMM algorithm, which combining the original algorithm with an ANFIS module, is presented in this paper.

3.1 PRINCIPLE OF THE IMPROVED ALGORITHM

From the analysis of original algorithm and the simulation result showed in Figure 1 (b) we can know that the target maneuvering will cause the observed covariance inconformity with the theoretical value of the Kalman residual, the tracking accuracy will decline rapidly and Kalman filter will diverge. Formula (6) shows the measurement noise covariance 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 Figure 2

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

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

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.

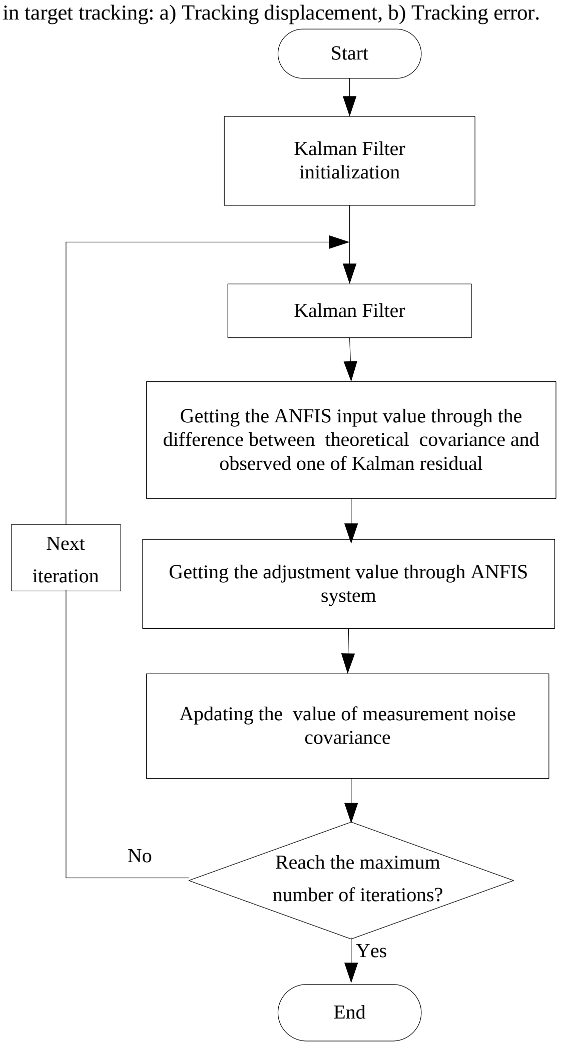


FIGURE 2 Flow chart of the improved algorithm.

Applying Adaptive [9] Neural-Fuzzy Inference System (ANFIS) can produce fuzzy rules and adjust membership functions automatically based on data without experience of experts. Based on those advantages of the ANFIS module mentioned above, the tracking accuracy is evidently increased in the improved algorithm by updating the value of system noise covariance in real-time.

The principle of the improved IMM algorithm is shown in Figure 3. $D(k)$ is the input parameter of the added ANFIS module, $\Delta R(k)$ will be adjusted to adapt to the target movement state variation.

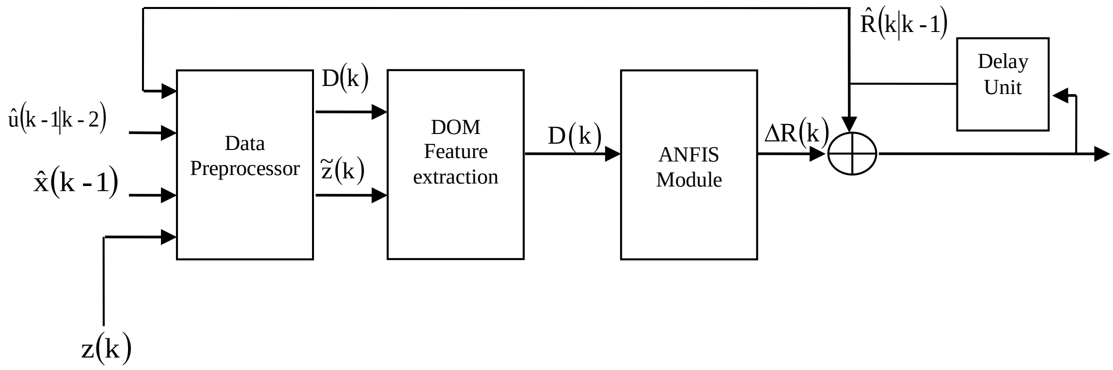


FIGURE 3 Principle of the improved algorithm.

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.

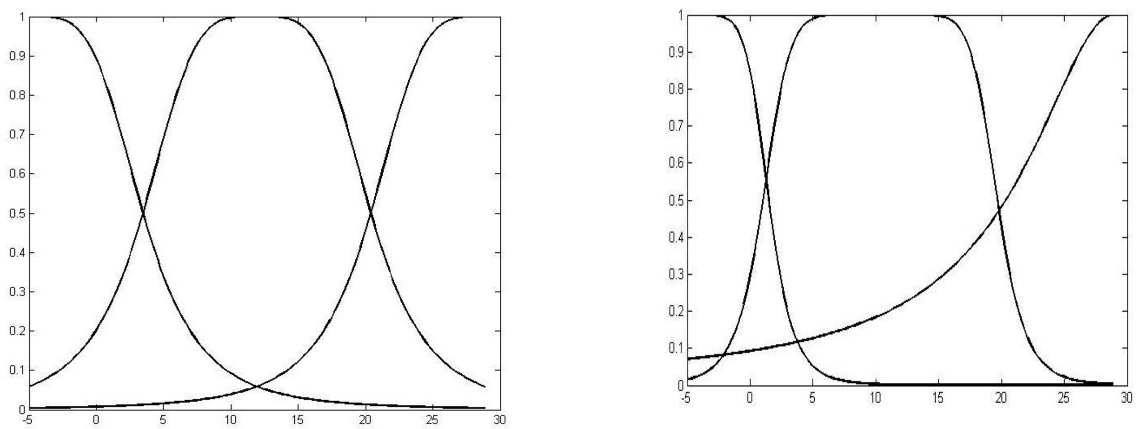
The variable $D(k)$ is defined as:

$$D(k) = S(k) - \hat{C}_2(k) \tag{13}$$

Measurement noise covariance can be updated as follows:

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

The input value is mapped into fuzzy sets in the universe of discourse. They are labelled as: $N = Negative$, $Z = Zero$, $P = Positive$. In this paper, the generalized bell shaped function has been chosen as the membership function to characterize fuzzy sets. The initial and final membership functions of the input parameter are showed as Figure 4:



a) b)

FIGURE 4 Initial and final generalized bell shaped membership: a) Initial membership functions, b) Final membership functions.

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. Finally, with these parameters defined above, the fuzzy rules [10] are expressed as follows:

Rule 1 *if* $D(k)$ is *N*, then $\Delta R(k)$ is *N*

Rule 2 *if* $D(k)$ is *Z*, then $\Delta R(k)$ is *Z*

Rule 3 *if* $D(k)$ is *P*, then $\Delta R(k)$ is *P*

Two data sets named $D(k)$ and $\Delta R(k)$ are generated by fuzzy rules mentioned above, which corresponding to the input and output parameters respectively for training of ANFIS. The parameters of ANFIS are showed as TABLE 1.

TABLE 1 ANFIS parameters

ANFIS info:
Number of nodes:16
Number of linear parameters:6
Number of nonlinear parameters:9
Total number of parameters:15
Number of training data pairs:110
Number of checking data pairs:0
Number of fuzzy rules:3

Because the fuzzy inference system based on Takagi-Sugeno is simple in algorithm and convenient to be realized, it is used in the two ANFIS modules. The generated ANFIS structure is showed as Figure 5.

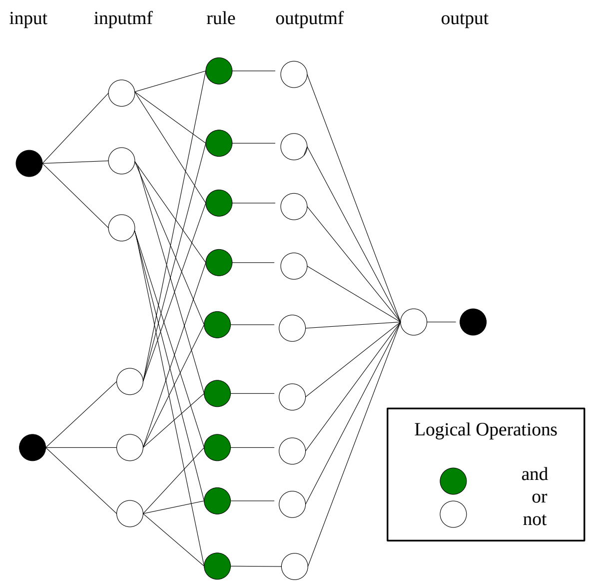


FIGURE 5 Structure of ANFIS

4 Experiments comparison of the two algorithms

4.1 EXPERIMENT RESULT COMPARISON

The improved Kalman filtering algorithm is applied to the simulation experiment of tracking maneuvering target. Both the initial state and the motion state of the target are the same as the previous experiment, that the initial position of the target is $(x, y) = (0m, 0m)$, the initial velocity is $(v_x, v_y) = (50m/s, 50m/s)$. An instantaneous acceleration $(a_x, a_y) = (10m/s, 10m/s)$ will be attached to the target at time instant $t = 20s$, lasting $2s$. And the sample time is also $T = 2s$. Figure 6 is the result of target tracking error. In this figure, the experiment errors of the improved Kalman filtering algorithm and the traditional one are compared.

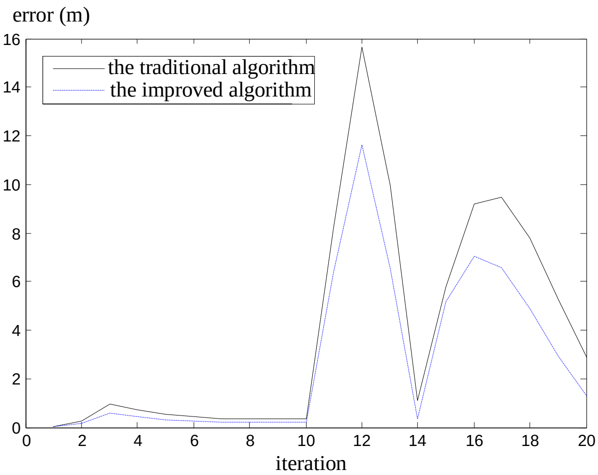


FIGURE 6. Comparison of the estimation error curves

The simulation result shows that the error of original Kalman filtering algorithm is very big and is reduced effectively by the improved algorithm when the speed of the moving target changes. So the loss of the moving target have been prevented owe to the improved algorithm.

4.2 EXPERIMENT ERROR ANALYSIS

The experiment error of the algorithms before and after improved are given in Table 2. It shows that the error of the improved algorithm has obviously decreased compared to the original algorithm from 11th iterations. In addition, the error of the improved algorithm is 3/5 of the original one in general. The reason of improved tracking accuracy is that the measurement noise covariance is compensated in real-time, and the observed covariance of Kalman residual is corrected when the acceleration of target is change.

TABLE 2 Experiment errors of the two algorithms

Iteration rounds	Error before improved (a)	Error after improved (b)	b/a
1	0.04535	0.02636	0.5812569
2	0.25667	0.14942	0.5821483
3	0.97354	0.58923	0.6052448
4	0.7369	0.43314	0.5877867
5	0.55952	0.32587	0.5824099
6	0.4435	0.25693	0.5793236
7	0.37398	0.21707	0.5804321
8	0.34496	0.20273	0.5876913
9	0.34515	0.20525	0.594669
10	0.35542	0.21134	0.5946204
11	8.21708	6.37459	0.7757731
12	15.64758	11.60113	0.7414009
13	9.93892	6.5259	0.6566005
14	1.1217	0.34532	0.3078541
15	5.7885	5.16354	0.8920342
16	9.2082	7.04156	0.7647054
17	9.48966	6.59441	0.6949048
18	7.77816	4.90665	0.630824
19	5.27737	2.94023	0.5571393
20	2.87997	1.29959	0.4512512
Average	3.9891065	2.770513	0.6174035

5 Conclusions

Firstly, the principle of the original Kalman filtering algorithm for maneuvering target tracking and its defects are introduced in this paper. Then, an improved Kalman filtering algorithm based on ANFIS is proposed. In the improved algorithm, because the value of measurement noise covariance is updated in real time by ANFIS module, the theoretical value of the Kalman residual covariance can keep space with the observed one. Finally, the simulation experiments are carried out and the tracking error are quantitatively analysed. The results show that the accuracy of the maneuvering target tracking has been increased obviously, when the original Kalman filtering algorithm is replaced with the improved one.

However, the improved algorithm still has some flaws. For example, the tracking accuracy of the improved algorithm will be influenced greatly by the parameters of ANFIS. So, further research is needed to gain the rules that how the parameters influence the tracking accuracy in the future.

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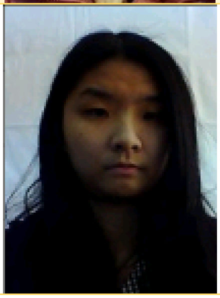	**Xingxing Zou, born 10.06.1993, Hunan province of China** **Current position, grades:** undergraduate student in the Shijiazhuang Tiedao University **University studies:** Bachelor degree will be earned in major of electronic and information engineering, Shijiazhuang Tiedao University in 2014. **Scientific interest:** digital signal processing.