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An Improved Interacting Multiple Model Algorithm for Target Tracking Based on ANFIS

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Abstract

IMM (Interacting Multiple Model) algorithm is widely used in target tracking, and its basic principle is described in detail at first. However, the IMM algorithm fails to obtain the prior probability of model conversion quickly and accurately when tracking for target. In this paper, an improved IMM algorithm based on ANFIS (the adaptive neural fuzzy inference system) is proposed. The improved algorithm can update the value of system noise covariance in real-time by ANFIS module through observing the coefficient of system noise covariance. Consequently, the probability of model conversion can be obtained more quickly and accurately. Then, the comparison and analysis of the experiment results between the original IMM algorithm and the improved one have been carried out. The experiment results show that the reaction rate for maneuvering target tracking is significantly boosted and tracking error is obviously reduced because the improved algorithm can update the value of system noise covariance in real-time and improve the system adaptability.

Keywords: *IMM (Interacting Multiple Model), ANFIS (the adaptive neural fuzzy inference system) System noise covariance, Probability of model conversion*

1. Introduction

Target tracking technique [1] is to obtain the unknown target motion parameters for processing and analysis, then estimating its motion state in real-time. Actually, the multiple model [2-5] algorithms is widely used for target tracking, and the IMM algorithm is considered to be one of the best algorithms[6] in actual application. The IMM algorithm was put forward by Bar-Shalom, the literature [7] showed that the tracking results of this algorithm are estimations of all the filters to be composed on the basis of some rules, and literature [8] proved that this algorithm has the ability to simplify complex issues and acquire a better result [9] that tracking precision has been improved.

The original IMM algorithm is of low tracking accuracy due to the limitation [10] that the IMM algorithm fails to obtain the prior probability of model conversion quickly and accurately. In order to overcome this limitation, Xiaohua, Nie proposed the AIMM (adaptive Interacting Multiple Model) algorithm [11], which made use of the state correlation of model to modify the model. However, the value of acceleration estimation affected the tracking accuracy. So it was necessary to definite the target acceleration in advance according to characteristics of target movement. In addition, Yaping,Qin[12] put forward a parameter adaptive algorithm, which adaptively adjusted the data update rate according to instantaneous maneuvering characteristics, but ,it increased the calculation amount. Then, Shiwen, Lei and Chi Ling, Wu [13] proposed a VSMM (variable structure IMM) algorithm [14] based on

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selection of different model sets at different times, but VSMM algorithm had complex structure and big computational complexity.

In order to overcome the defect of low tracking accuracy in the IMM algorithm, the paper proposes an improved IMM algorithm based on ANFIS and utilizes the fuzzy inference to estimate model probability. The ANFIS module that combining fuzzy logic inference with neural network can update the value of system noise covariance in real-time[15-17].The experiment results show that the reaction rate for getting accurate probability of model conversion is significantly boosted and tracking accuracy is evidently increased after the original IMM algorithm was substituted by the improved one.

2. Principle and Defect of the Original IMM Algorithm

2.1. Principle of the IMM Algorithm

It is assumed that the model set of the original IMM algorithm includes two kinds of tracking model: CV (Constant Velocity) and CT (Coordinate Turn). Its operation principle is shown as Fig.1, from which it can be known that at the IMM algorithm includes two filters of M1 and M2, an estimator of model probability, a fusion estimator [18-19] and interactive effectors.

In the original IMM algorithm, $\hat{X}_1(k-1|k-1), P_1(k-1|k-1)$ and $\hat{X}_2(k-1|k-1), P_2(k-1|k-1)$ are filter results of two models at previous time. $\hat{X}_1^0(k-1|k-1), P_1^0(k-1|k-1)$ and $\hat{X}_2^0(k-1|k-1), P_2^0(k-1|k-1)$ are the re-initialized state vector and covariance matrix. $Z(k)$ is the new target measurement vector at k moment. $\hat{X}_1(k|k), P_1(k|k)$ and $\hat{X}_2(k|k), P_2(k|k)$ are the updated state estimation and error covariance for two filters. $\wedge_1(k)$ and $\wedge_2(k)$ are likelihood functions of the two filters when calculating new target measurement vector $z(k)$ and matched model $m^{(i)}(k)$ at k moment.

Operation principle of the original IMM algorithm can be drawn as follows. Supposing that a model of CV or CT is the same as target motion state at k moment, he initial state of its corresponding filter can be worked out based on the previous filter output. According to the formula (2-1) and (2-2). Then, each model will be filtered parallelly, and their model probabilities of $u^{(i)}(k)$ will be updated as formula (2-3). Finally, the state estimation of $\hat{X}(k|k)$ and error covariance matrix of $P(k|k)$ will be gained according to the formula (2-4) and (2-5).

$$\bar{x}^{(j)}(k-1|k-1) \overset{def}{=} E\left(x(k-1)|m^{(j)}(k), Z^{k-1}\right) = \sum_{i=1}^{r} \hat{x}^{(i)}(k-1|k-1)\mu^{(i,j)}(k-1|k-1) \tag{2-1}$$

$$\begin{aligned}\bar{P}^{(j)}(k-1|k-1) &= \sum_{i=1}^{2}[P^i(k-1|k-1) + (\hat{x}^{(j)}(k-1|k-1) - \bar{x}^{(j)}(k-1|k-1)) \\ &(\hat{x}^{(j)}(k-1|k-1) - \bar{x}^{(j)}(k-1|k-1)^T]\mu^{(i,j)}(k-1|k-1)\end{aligned} \tag{2-2}$$

$$\mu_i(k) = P(m^{(i)}(k)|Z^k) = \frac{1}{c}\Lambda^{(i)}(k)\bar{c}_i, \quad i = 1,2,3\ldots \tag{2-3}$$

$$\hat{x}(k|k) = \sum_{i=1}^{r} \bar{x}^{(i)}(k|k)\mu^{(i)}(k) \tag{2-4}$$

$$P(k|k)=\sum_{i=1}^{r}[P^{(i)}(k|k)+(\hat{x}^{(i)}(k|k)-\overline{x}^{(i)}(k|k))(\hat{x}^{(i)}(k|k)-\overline{x}^{(i)}(k|k))^{\mathrm{T}}]\mu^{(i)}(k) \tag{2-5}$$

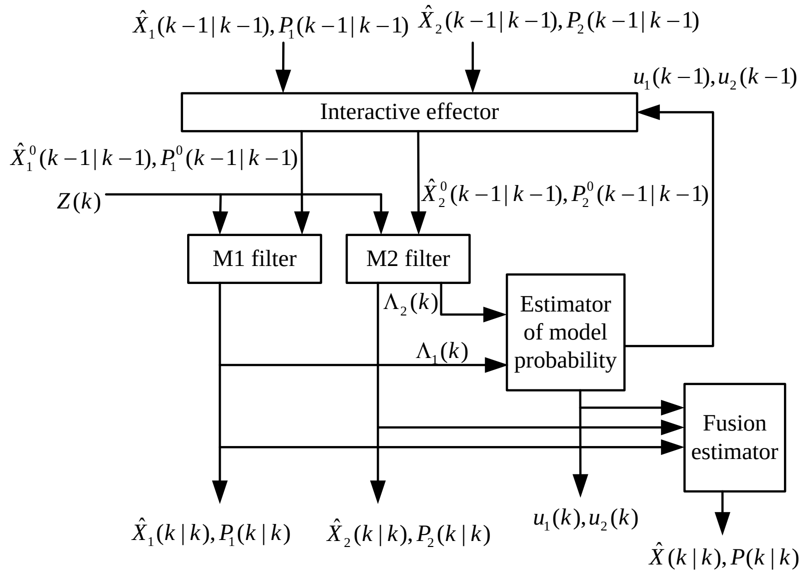


Figure 1. Principle of the Original Algorithm

2.2 Limitation of the Original IMM Algorithm

In general, there are two factors that influence the target tracking accuracy of the IMM algorithm. One is the number of the tracking models; the other is their matching degree with the target movement state. Because the models number in an IMM algorithm is a fixed value, their matching degree with the target movement state is a major factor that influence the target tracking accuracy. Low tracking accuracy for maneuvering target is a fatal limitation of the original IMM algorithm, the reason for which is that its model set cannot match the rapidly changing target movement state and the model conversion probabilities cannot be obtained accurately and quickly. The following experiment is to illustrate the limitation of the algorithm.

In this experiment, the model set of the original IMM algorithm includes two kinds of tracking model: CV and CT. The angular velocity of CT model is $-\pi/120$ rad/s, system noise covariance for CV model is $Q_2=[0.0144^2\ \ 0;0\ \ 0.0144^2]$, and system noise covariance for CT model is $Q_1=[0.1^2\ \ 0;0\ \ 0.1^2]$. Assuming that the initial position of the target is $(x,y)=(1000m,1000m)$, target moves with the constant velocity of $(v_x,v_y)=(3m/s^2,3m/s^2)$ until T=50s. Then, an acceleration $(a_x,a_y)=(1m/s^2,0.3m/s^2)$ is attached to the target, this acceleration continues until T=100s. Next, the target turns with an angular velocity of $\pi/240\ \ rad/s$ until T=250s, and moves with the constant velocity until T=300s. Finally, the target turns with an angular velocity of $-\pi/120\ \ rad/s$ to the end of simulation at time T=400s. After 50 independent Monte Carlo runs the simulation results are shown as follows.

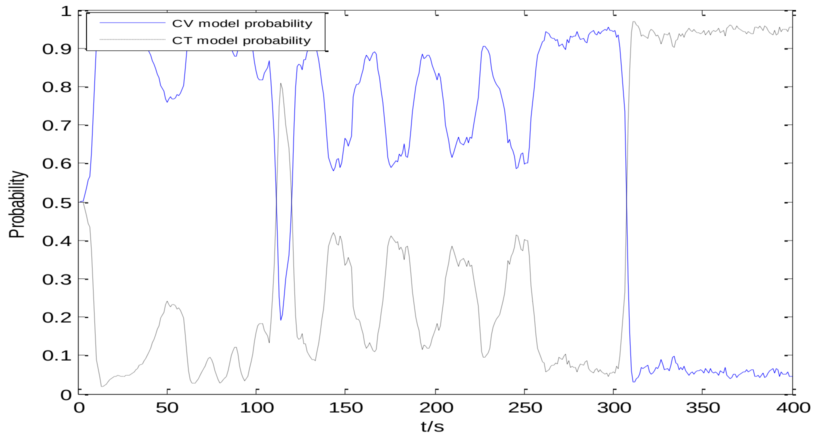


Figure 2. Model Probability of the IMM Algorithm

Figure 2 shows model probabilityy values of CV model and CT model during the target tracking process of 400s:

From the beginning to 100s, CV model probability is much higher than CT model. It shows that CV model has a high matching degree with the target motion state and plays a major role during the time period. According to the same rule, CV model play a major role during the time of 251s to 300s and CT model play a major role during the last 100s.

From the time 101s to 250s, the probability cures of CV model and CV model fluctuate strongly. It shows that neither of two models has a high matching degree with the target motion state and their model probabilityy values must be adjusted in real time to adapt to the rapid change of the motion state.

Through careful observation of the curves in Figure 2, a limitation of the original IMM algorithm can be drawn that the adjustment of their model probabilityy values lags behind the motion state variation. For example, target movement pattern changes from the constant velocity to an angular velocity at the moment of 300s, but the adjustment of the model probabilityy values delay for a few seconds. Therefore, getting the model conversion probabilities synchronously with the motion state variation is a critical method to remedy the limitation of the original IMM algorithm.

3. The improved IMM Algorithm

To overcome the limitation that the original IMM algorithm fails to obtain the prior probability of model conversion quickly and accurately, an improved IMM algorithm, which combining the original IMM algorithm with an ANFIS module, is presented in this paper.

Based on the simulation experiments, a group of fuzzy rules in the ANFIS module have been designed. As the output parameter of the ANFIS module, the coefficient of system noise has been updated in real-time and the model conversion probabilities do not lag behind the motion state variation any more. The following experiment results shows that the limitation of the original IMM algorithm has been remedied and the target tracking accuracy has been increased more obviously in the improved IMM algorithm.

3.1 Principle of the Improved Algorithm

Applying Adaptive [20] 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.

Supposing the improved IMM algorithm includes two kinds of tracking model: CV and CT still, its principle is shown in Fig.3. The model probabilities $(u_1(k), u_2(k))$ are the input parameters of the two newly added ANFIS modules respectively. After being multiplied by their output parameters $(f_1(k), f_2(k))$, the system noise covariance (Q) will be adjusted to adapt to the target movement state variation.

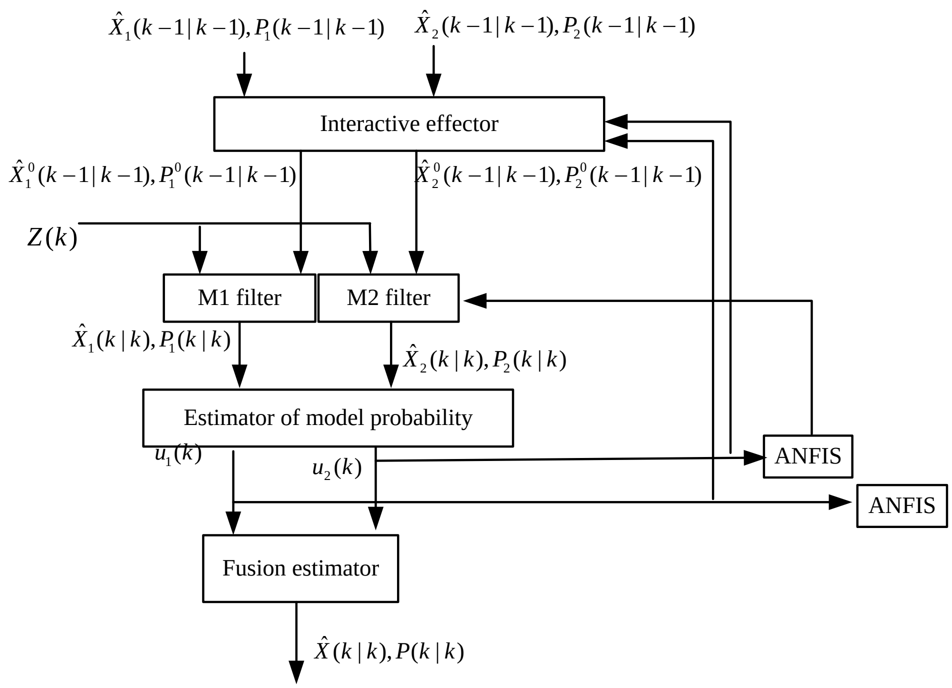


Figure 3. Principle of the Improved Algorithm

Formula (3-1) and (3-2) shows the computing process of the error covariance in the original IMM algorithm and the improved one respectively.

$$\overline{P}^{(i)}(k|k-1) = F(k)P^{(i)}(k-1|k-1)F^T(k) + Q^{(i)}(k-1) \tag{3-1}$$

$$\overline{P}^{(i)}(k|k-1) = F(k)P^{(i)}(k-1|k-1)F^T(k) + f^{(i)}Q^{(i)}(k-1) \tag{3-2}$$

In formula (3-1) and (3-2), $Q^{(i)}(k-1)$ is the system noise covariance of CT or CV model. $f^{(i)}$ is the output parameters of ANFIS model to adjust the system noise covariance (Q) according to $f^{(i)}Q^{(i)}(k-1)$.Then, the current state estimation ($\hat{x}(k|k)$) and state error covariance ($P(k|k)$) for all targets are also updated to increase the tracking precision.

3.2 Design of ANFIS System

3.2.1 Filter Model and Filter Method

In the improved algorithm, two Kalman filters are used to predict the target movement state of $\hat{x}(k|k)$.

3.2.2 Parameters Initialization of ANFIS module

① Fuzzification of the input parameters: The input parameters of ANFIS modules are CV model probability of u1 and CT model probability of u2 respectively, and their value range are both [0, 1]. They are fuzzily processed and their respective membership functions (ZE=Zero, MP=Middle Positive, LP=large Positive) are initialized as Figure 9 (a) and (b).

② Fuzzification of the output parameters: The output parameters of ANFIS modules are f_1 and f_2 respectively, and their value range are both [0.1, 2.7]. They are also fuzzily processed and their respective membership functions are ZE=Zero, MP=Middle Positive and LP=large Positive.

③ Selection of the membership function: The bell function has been chosen as the membership function to characterize fuzzy sets in this paper.

④ Selection of the fuzzy inference system: 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 4.

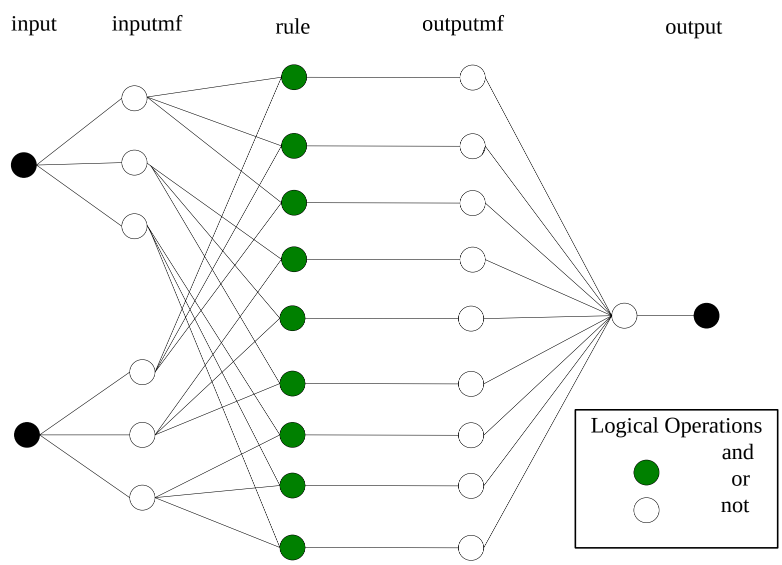


Figure 4. Structure of ANFIS

Table 1 shows the parameters and their values used in the ANFIS training process.

Table 1. ANFIS Parameters

Parameters Name.	Value
Type of input MF	Gbell
Type of output MF	Linear
Number of input MF	3
Number of Epoch	1000
Learning method	Hybrid
Number of training data pairs	403

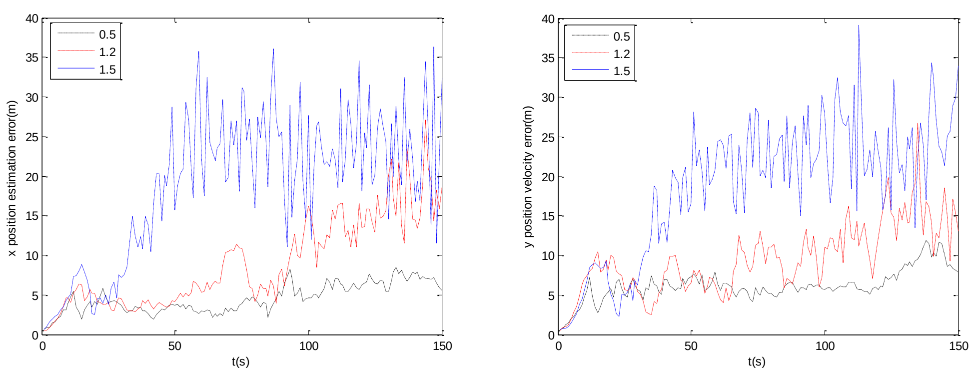
3.2.3 Fuzzy Rule Base

3.2.3.1 Basis for Fuzzy Rules Design

The system noise covariance (Q) is a parameter in target tracking algorithm, and it has a great impact on the tracking accuracy. Thus, its quantitative impact on the tracking accuracy can be used as the theoretical basis for fuzzy rules design. Its quantitative impact on the tracking accuracy is introduced as follows in two difference cases: tracking model matching target movement mode or not.

(1) The case of tracking model matching target movement mode

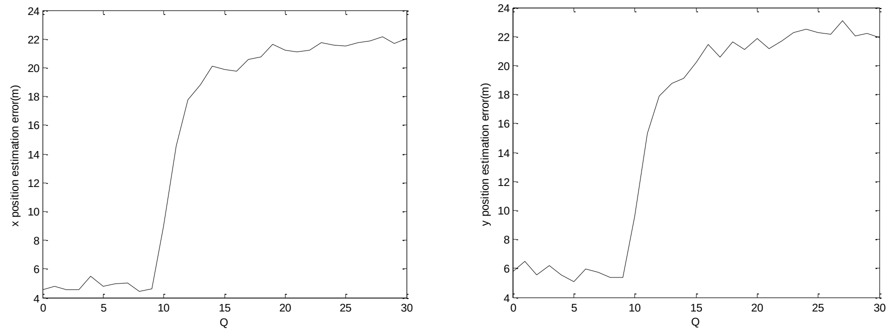
In the following experiments, the tracking models include CV and CT. Their system noise covariance are Q_1=[0.1^2 0; 0 0.1^2] and Q_2=[0.0144^2 0; 0 0.0144^2], and their coefficients are f_1 and f_2 respectively, which are showed in formula (3). It is assumed that the initial position of target is $(x, y) = (1000m, 1000m)$, the initial velocity is $(v_x, v_y) = (10m/s, 10m/s)$, the target turns with an angular velocity of $-\pi/120\,rad$ until the end of simulation at time T=150s and the sample time is T=1s. Figure 5 shows the position error curves under the condition of different f_1 and f_2.



(a) Position error comparison on Axis-X (b) Position error comparison on Axis-Y

Figure 5. Position Error Under the Condition of Different f1 and f2

Figure 5 shows that deference f_1 and f_2 have obvious impact on the position errors: the larger are their values, the bigger the position errors. Because f_1 and f_2 are used to worked out the updated system noise covariance of $f^{(i)}Q^{(i)}(k-1)$ and their value range are both [0.1, 3.1], how the system noise covariance of Q impact the position errors can be gained and shown in Figure 6.

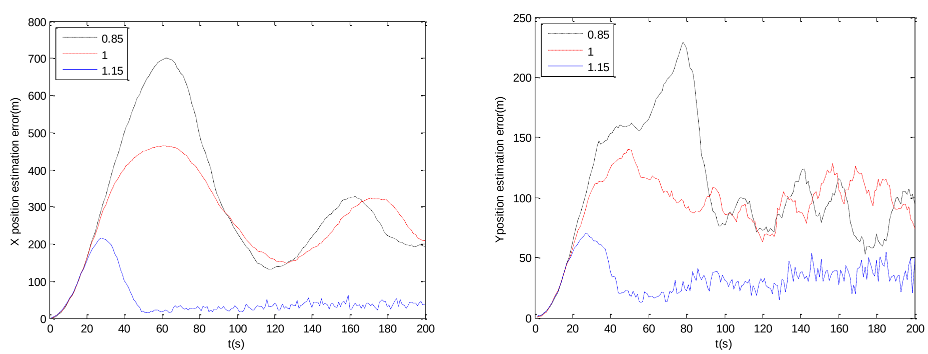


(a) Position error comparison on Axis-X (b) Position error comparison on Axis-Y

Figure 6. Position Error under the Condition of Different Q

(2) The case of tracking model not matching target movement mode

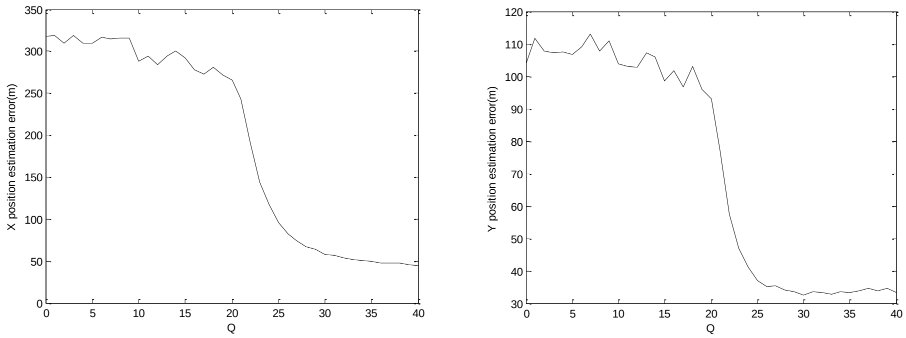
In this case, all experimental conditions except the target movement state are same with that in the previous case. It is assumed that the initial position of target is $(x, y) = (1000m, 1000m)$, the initial velocity of $(v_x, v_y) = (3m/s, 3m/s)$, the acceleration is $(a_x, a_y) = (1m/s^2, 0.3m/s^2)$ and the sample time is T=1s. Figure 7 shows the position error curves under the condition of different f_1 and f_2.



(a) Position error comparison on Axis-X (b) Position error comparison on Axis-Y

Figure 7. Position Error under the Condition of Different f1 and f2

Figure 7 shows that deference f_1 and f_2 have obvious impact on the position errors: the larger are their values, the less the position errors. Because f_1 and f_2 are used to worked out the updated system noise covariance of $f^{(i)}Q^{(i)}(k-1)$ and their value range are both [0.8, 1.2], how the system noise covariance of Q impact the position errors can be gained and shown in Figure 8.



(a) Position error comparison on Axis-X (b) Position error comparison on Axis-Y

Figure 8. Position Error under the Condition of Different Q

From the experimental results in the two cases above, the theoretical basis for fuzzy rules design can be drawn as follows:

(1)When tracking model matches movement target mode, the value of system noise covariance (Q) should be reduced to increase the tracking accuracy.

(2)When tracking model does not match movement target mode, the value of system noise covariance (Q) should be increased to increase the tracking accuracy.

3.2.3.2 Fuzzy Rules Design

In general, fuzzy rules [21] are described as "if-then statements". According to the theoretical basis that drawn in the above part, eighteen fuzzy rules were designed and used in ANFIS modules to update the output parameters of f_1 and f_2. Because the nine fuzzy rules related to f_1 are similar with another nine fuzzy rules related to f_2, they are illustrated as an example in the following sections.

R_1：*If* u_1 *is ZE and* u_2 *is ZE, then* f_1 *is LP*；

R_2：*If* u_1 *is ZE and* u_2 *is MP, then* f_1 *is LP*；

R_3：*If* u_1 *is ZE and* u_2 *is LP, then* f_1 *is LP*；

R_4：*If* u_1 *is MP and* u_2 *is ZE, then* f_1 *is LP*；

R_5：*If* u_1 *is MP and* u_2 *is MP, then* f_1 *is MP*；

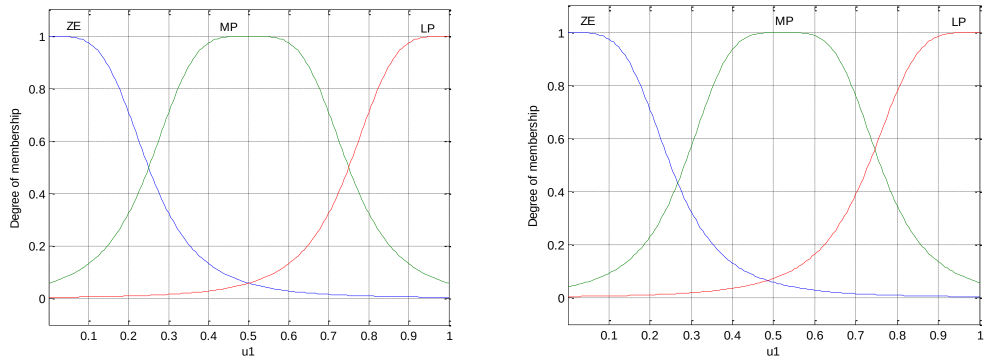
R_6：*If* u_1 *is MP and* u_2 *is LP, then* f_1 *is LP*；

R_7：*If* u_1 *is LP and* u_2 *is ZE, then* f_1 *is SP*；

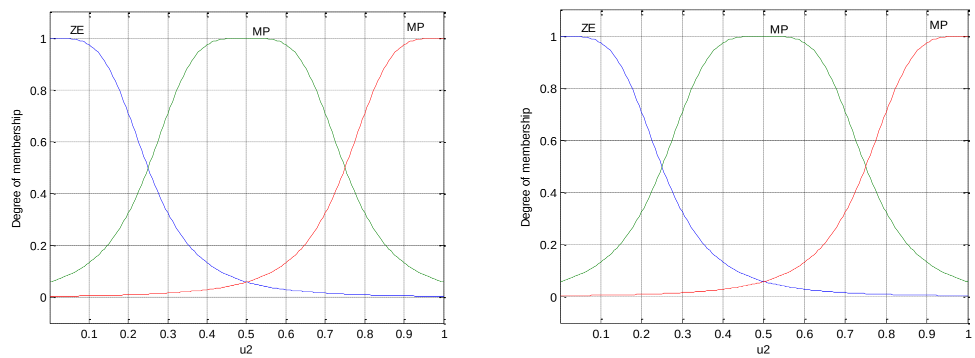
R_8：*If* u_1 *is LP and* u_2 *is MP, then* f_1 *is MP*；

R_9：*If* u_1 *is LP and* u_2 *is LP, then* f_1 *is SP*；

Among the fuzzy rules above, u_1 and u_2 are CV model probability and CT model probability respectively. *ZE, SP, MP* and *LP* are membership functions and f_1 is the coefficient of system noise covariance for CV model. According to the fuzzy rules, a set of data are generated to train the corresponding ANFIS module. Figure 9 is membership functions of two ANFIS models and Figure 10 is output surface chart for coefficient of system noise covariance after training.

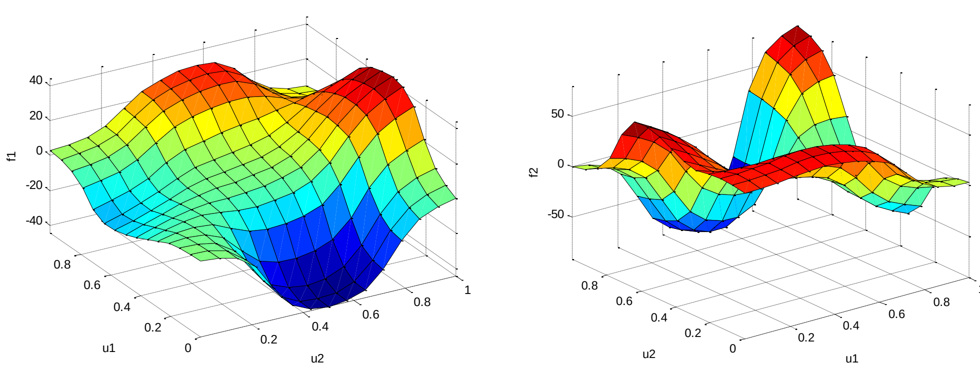


(a) MFs for CV model before training (b) MFs for CV model after training



(a) MFs for CT model before training (b) MFs for CT model after training

Figure 9. MFs (Membership Functions) in the ANFIS Modules before and after Training

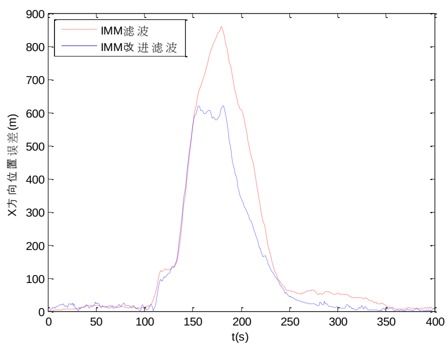


(a)Input-output relations for CT model (b)Input-output relations for CT model

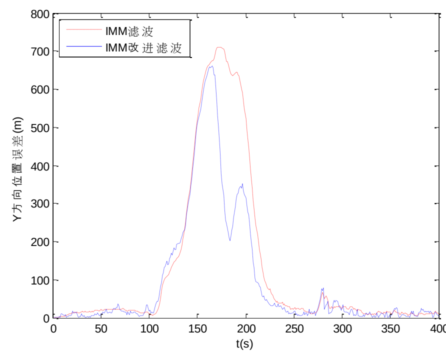
Figure 10. Input-output Relations in the ANFIS After Training

4. Experiment Results Comparison between the Original Algorithm and the Improved One

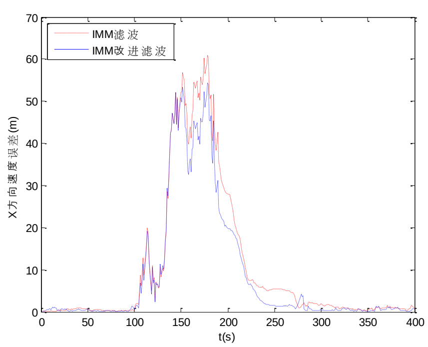
In the following experiments, it is assumed that the initial position of the target is $(x, y) = (1000m, 1000m)$, target moves with the constant velocity of $(v_x, v_y) = (10m/s, 10m/s)$ until T=100s. Then, an acceleration $(a_x, a_y) = (1m/s^2, 1m/s^2)$ is attached to the target, this acceleration continues until *T*=190*s*. Next, the target turns with an angular velocity of $-\pi/270\,rad$ until T=270s. Finally, the target move with the constant velocity to the end time *T*=400*s*. Figure 11 shows the position error comparisons and the velocity error comparisons between the two algorithms.



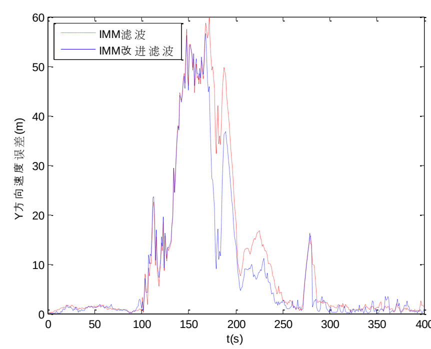
(a) Position error comparison on Axis-X



(b) Position error comparison on Axis-Y



(c) Velocity error comparison on Axis-X

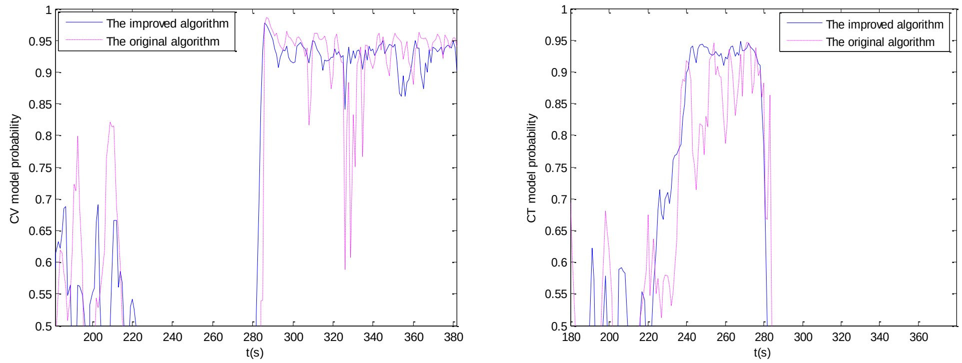


(d) Velocity error comparison on Axis-Y

Figure 11. Tracking Error Comparisons between the Original Algorithm and the Improve One

Figure 11 shows that :(1) Under the condition of non-maneuvering, the position error and velocity error between the two algorithms are both very small, although that in the improved one are slightly lower.

(2) while the target is under the condition of maneuvering state, especially being attached with an acceleration within 101s to190s, the position error and velocity error in the improved algorithms are much more less than that in the original one, although they are both larger than that under the condition of maneuvering state.



(a) Comparison of CV model (b) Comparison of CT model

Figure 12. Comparison of the Model Conversion Probabilities between the Improved Algorithm and the Original One

In Figure 12, the curves of the improved algorithm are steeper than that of the original one at the moment when the target motion state is varying. It shows that the model conversion probabilities in the improved algorithm can be adjusted more quickly than that in the original one because of the ANFIS modules. For example, when the target motion state is varying at time T=270s, the CV model probability rising to the right value is much quicker in the improved algorithm than the original one, and the CT model probability declining to the appropriate value is much quicker in the improved algorithm than the original one , too.

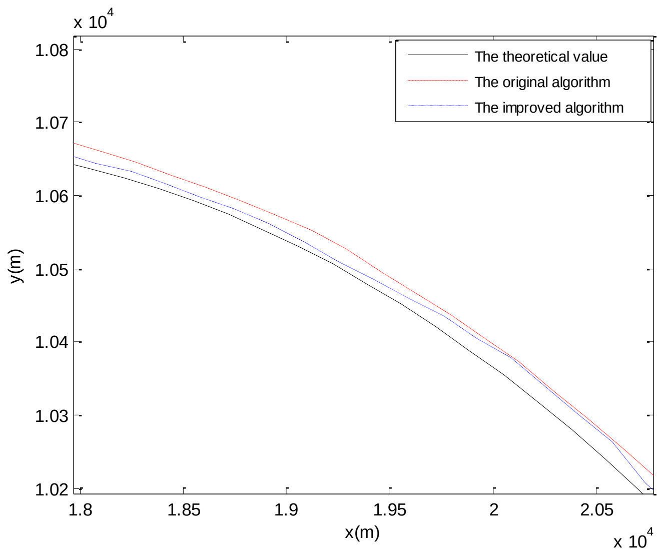


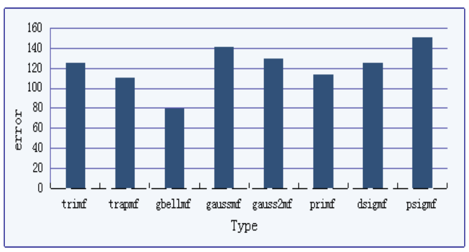
Figure 13. Comparisons of the Racking Trajectory between the Two Algorithms

Figure 13 shows that the ANFIS model can update the system noise covariance of Q more quickly and the tracking error will be reduced significantly when the original algorithm is replaced by the improved one. The tracking error is worked out by extracting a root of the position error square on axis-Y and axis-X, by this way, the tracking errors of the improved algorithm and the original one are 152.2338m and 213.6264m respectively. Obviously, the improved algorithm has higher tracking precision than the original one.

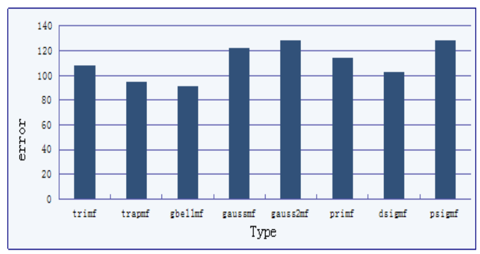
5. Parameter Optimization in the ANFIS Module

Generally, the training parameters in ANFIS module have an effect on the tracking accuracy. According to the following experiments, two parameters of MF type and MF number have the most impact and the corresponding appropriate training parameters were selected out.

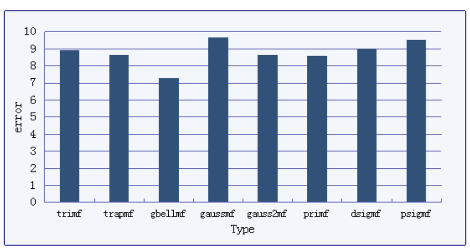
In the following experiments, the initial position and the motion state of the target are the same with that in Section 4 above. Eight types of MF are "trimf", "trapmf", "gbellmf", "gaussmf", "gauss2mf", "pimf", "dsigmf" and "psigmf". Fig. 14 shows the average tracking error based on different MF types under the same condition. It can be seen that the average tracking error is the least When the gbell membership function is used in proposed algorithm. So the most optimal MF type should be gbell in the improved IMM algorithm.



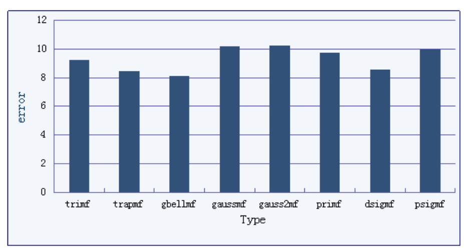
(a) Position error comparison on Axis-X



(b) Position error comparison on Axis-Y



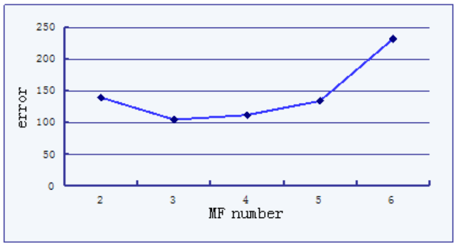
(c) Velocity error comparison on Axis-X



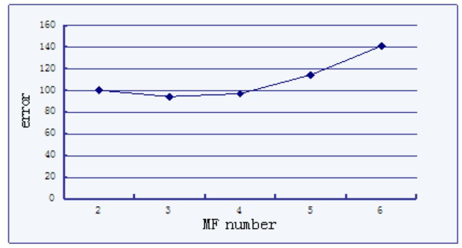
(d) Velocity error comparison on Axis-Y

Figure 14. Average Tracking Error Comparison for Different Types of MF

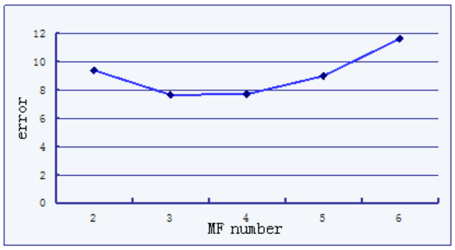
Except for the MF type, the parameter of MF number also has obvious impact on the target tracking accuracy. Using gbell as the MF function, Figure 15 shows the average tracking error based on the different MF number of 2, 3,4,5,6 respectively. It can be seen that the average tracking error is the least when the MF number is 3. Therefore, the most optimal MF number should be 3 in the improved IMM algorithm.



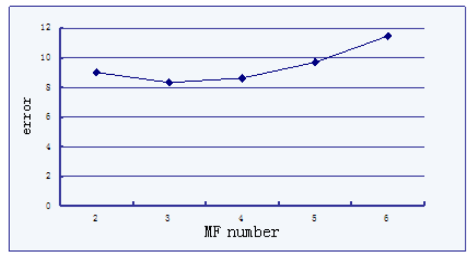
(a) Position error comparison on Axis-X



(b) Position error comparison on Axis-Y



(c) Velocity error comparison on Axis-X



(d) Velocity error comparison on Axis-Y

Figure 15. Average Tracking Error Comparison for Different MF Number

6. Conclusions

After the principle of the original IMM algorithm for target tracking is introduced and its defects are analyzed, an improved IMM algorithm based on ANFIS is proposed in this paper. In the improved algorithm, the system noise covariance is updated in real-time by ANFIS module and the probability of model conversion is calculated out quickly and accurately. Then, the simulation experiments are carried out and the tracking error are analyzed quantitatively. The experiment results show that the improved algorithm can update the system noise covariance and accelerate model conversion rate in real-time. Compared with the original one, the improved IMM algorithm can obtain the accurate probability of model conversion more quickly and the accuracy of target tracking has been improved more obviously.

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