IMM Method Using Intelligent Input Estimation for Maneuvering Target Tracking

Bum Jik Lee*, Young Hoon Joo**, and Jin Bae Park*

* Department of Electrical and Electronic Engineering, Yonsei University, Seoul, Korea
(Tel : 82-2-2123-2773; E-mail : bumjik@control.yonsei.ac.kr, jbpark@yonsei.ac.kr)
**School of Electronic and Information Engineering, Kunsan National University, Cheonbuk, Korea
(Tel : 82-63-469-4706; E-mail : yhjoo@kunsan.ac.kr)

Abstract: A new interacting multiple model (IMM) method using intelligent input estimation (IIE) is proposed to track a maneuvering target. In the proposed method, the acceleration level for each sub-model is determined by IIE-the estimation of the unknown acceleration input by a fuzzy system using the relation between maneuvering filter residual and non-maneuvering one. The genetic algorithm (GA) is utilized to optimize a fuzzy system for a sub-model within a fixed range of acceleration input. Then, multiple models are composed of these fuzzy systems, which are optimized for different ranges of acceleration input. In computer simulation for an incoming ballistic missile, the tracking performance of the proposed method is compared with those of the input estimation (IE) technique and the adaptive interacting multiple model (AIMM) method.

Keywords: intelligent input estimation, maneuvering target, fuzzy system, genetic algorithm, input estimation technique, adaptive interacting multiple model method

1. INTRODUCTION

Maneuvering target tracking, which is considered as an adaptive filtering problem including the uncertainty of target model caused by the acceleration, has been studied in the field of state estimation over decades. The Kalman filter has been widely used as a tracking filter to estimate the position, the velocity, and the acceleration of a target, but in the presence of a maneuver, its performance may be seriously degraded. To solve this difficulty, various techniques have been investigated and applied. First, in 1970, Singer proposed a target tracking model in which maneuver was assumed as the first order Markov process with time correlation [1]. Since the Singer's method, recent researches are roughly divided in two main approaches. One approach is to detect the maneuver and then to cope with it effectively. Examples of this approach include the input estimation (IE) technique [2], the variable state dimension (VSD) approach [3], and so on. The other approach is to describe the motion of a target with multiple models. The interacting multiple model (IMM) method [4] and the adaptive IMM (AIMM) method [5] are included in this approach. In this paper, the second approach is mainly discussed.

The accuracy of maneuvering target tracking using multiple models relies upon the suitability of each target motion model to be used for a maneuver. In the IMM method, the estimate is obtained by a weighted sum of the estimates from sub-models in accordance with the probability of each model being effective. But, to construct multiple models, this method requires predefined sub-models with the different dimensions or process noise levels in consideration of the properties of the maneuvers. On the other hand, the AIMM method needs no predefined sub-models because it estimates the acceleration of the target adaptively and constructs multiple models using this estimated acceleration. In this algorithm, a two-stage Kalman estimator [6], which has a bias-free filter and a bias filter, is used only in estimating the acceleration. However, the acceleration intervals, which are symmetrically added to or subtracted from the estimated acceleration value to construct multiple models, should also be determined by the properties of the maneuvers.

In this paper, to relax these prior requirements of the conventional maneuvering target tracking methods, improve the tracking performance, and establish the systematic tracker design procedure for a maneuvering target, we propose an IMM method using intelligent input estimation (IIE). In the proposed method, the acceleration level for each sub-model is determined by the IIE. The IIE means the estimation of the unknown acceleration input within a fixed range by a fuzzy system using the relation between maneuvering filter residual and non-maneuvering one. The genetic algorithm (GA) is utilized to optimize a fuzzy system for a sub-model within a fixed range of acceleration input. Then, multiple models are composed of these fuzzy systems, which are optimized for different ranges of acceleration input.

This paper is organized as follows: Section 2 describes target model and summarizes the AIMM method as preliminaries, and the details of the IIE and the IMM method using IIE are described in section 3. In section 4, the tracking performance of the proposed method is compared with those of the input estimation (IE) technique and the AIMM method. Conclusions are finally drawn in section 5.

2. PRELIMINARIES

2.1 Target model

The linear discrete time models for a maneuvering target and a non-maneuvering target are described for each axis by

$$X(k+1) = FX(k) + G[u(k) + w(k)] \tag{1}$$

$$X(k+1) = FX(k) + Gw(k) \tag{2}$$

$$F = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix},\quad G = \begin{bmatrix} T^2/2 \\ T \end{bmatrix}$$

where $X(k) = [p\ \dot{p}]' = [p\ v]'$ is the state vector, F and G are the transition matrix and the excitation matrix, respectively, $w(k)$ is the process noise, and $u(k)$ is the unknown acceleration input. The measurement equation is

$$Z(k) = HX(k) + v(k) \tag{3}$$

where $H = [1\ 0]$ is the measurement matrix and $v(k)$ is the measurement noise. $w(k)$ and $v(k)$ are considered as white Gaussian noise sequences with zero-mean and variances q and r, and their correlation is assumed to be zero.

2.2 AIMM method

The AIMM method has a limited number of sub-models for each axis, and each sub-model is represented as the estimated acceleration or the acceleration levels distributed symmetrically about the estimated one [5]. In the case of N sub-models for each axis, the set of multiple models is represented as

$$M_A = \{\hat{a}_1(k),\ \hat{a}_2(k),\ \cdots, \hat{a}_N(k)\}$$
$$= \{\hat{a}(k), \hat{a}(k) \pm \varepsilon_1, \cdots, \hat{a}(k) \pm \varepsilon_{(N-1)/2}\}$$

where $\hat{a}(k)$ is the estimated acceleration and $\varepsilon_{(N-1)/2}$ is the predetermined acceleration interval.

Figure 1 describes the AIMM method with N sub-models.

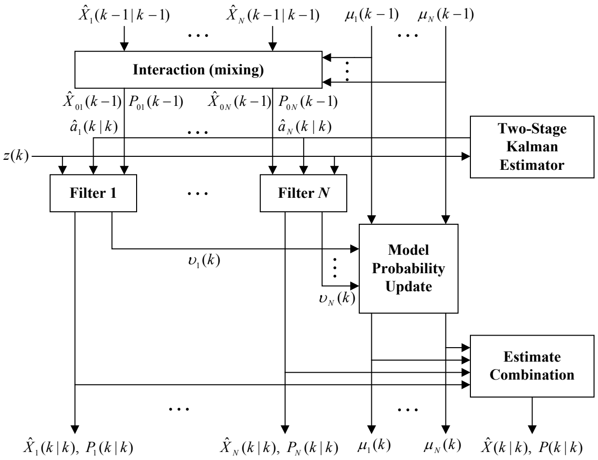


Fig. 1 AIMM method

3. IMM METHOD USING INTELLIGENT INPUT ESTIMATION

3.1 IIE

In this paper, we propose an IMM method using IIE to relax the prior requirements of the conventional multiple model methods, and improve the tracking performance. The acceleration level for each sub-model is determined by the IIE. The IIE means the estimation of the unknown acceleration input within a fixed range by a fuzzy system using the relation between maneuvering filter residual and non-maneuvering one. The $j\,(j = 1, \cdots, M)$ th fuzzy rule for a sub-model is represented by

R_j : If χ_1 is A_{1j} and $\chi_2(k)$ is A_{2j}, then y is $\hat{u}_j$

where two input variables, χ_1 and χ_2, are the non-maneuvering filter residual $\upsilon^*(k)$ and the difference between non-maneuvering filter residual $\upsilon^*(k)$ and maneuvering filter residual $\upsilon(k-1)$, respectively. A consequent variable y is the estimated acceleration input $\hat{u}_j$ for the j th fuzzy rule. The Gaussian membership function A_{ij} with the center c_{ij} and the standard deviation σ_{ij} has the following membership grade.

$$\theta_{A_{ij}}(\chi_i) = \exp\left[-\frac{1}{2}\left(\frac{\chi_i - c_{ij}}{\sigma_{ij}}\right)^2\right] \quad (4)$$

The unknown acceleration input $\hat{u}(k)$ can be estimated in the following form.

$$\hat{u}(k) = \frac{\sum_{j=1}^{M} \hat{u}_j \left(\prod_{i=1}^{2} \theta_{A_{ij}}(\chi_i(k))\right)}{\sum_{j=1}^{M} \left(\prod_{i=1}^{2} \theta_{A_{ij}}(\chi_i(k))\right)} \quad (5)$$

According to the universal approximation theorem [7], there exist optimal parameters c_{ij}, σ_{ij}, and $\hat{u}_j$, which can approximate $\hat{u}(k)$ as closely as possible. In this paper, the GA is applied to optimize the parameters in both the premise part and the consequence part of the fuzzy system simultaneously. Obviously the fuzzy system should be designed such that the difference between the actual acceleration input and the estimated one is minimized.

$$E = \sum_k \left(u(k) - \hat{u}(k)\right) \quad (6)$$

The GA represents the searching variables of the given optimization problem as a chromosome containing one or more sub-strings. In this case, the searching variables are the center c_{ij} and the standard deviation σ_{ij} for a Gaussian membership function of the fuzzy set A_{ij} and the singleton output $\hat{u}_j$. A convenient way to convey the searching variables into a chromosome is to gather all searching variables associated with the j th fuzzy rule into a string and to concatenate the strings as

$$S_j = \{c_{1j},\ \sigma_{1j},\ c_{2j},\ \sigma_{2j},\ \hat{u}_j\}$$
$$S = \{S_1,\ S_2,\ \cdots,\ S_M\}$$

where S_j is the real coded parameter sub-string of the j th fuzzy rule in an individual S. At the same time and to identify the number of fuzzy rules, we utilize the binary coded rule number string, which assigns a 1 or 0 for a valid or invalid rule, respectively. Figure 2 illustrates the structure of a chromosome.

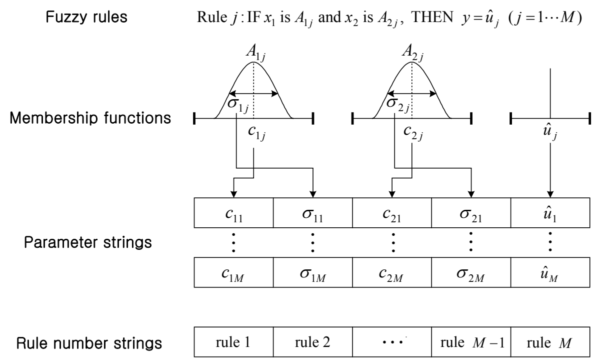


Fig. 2 Structure of a chromosome

Each individual is evaluated by a fitness function. We use the fitness function of the form

$$\text{fitness} = \frac{\lambda}{E+1} + \frac{1-\lambda}{M+1} \quad (7)$$

where λ is a positive scalar, to adjust the weight between the error and the rule number.

The GA that optimally estimates the unknown acceleration input in the proposed method is summarized as follows [9-12].

Step 1: Set the parameters for the GA (maximum generation number, maximum rule number, population size, crossover rate, and mutation rate).

Step 2: Randomly generate the initial population such that all searching variables exist within the search space.

Step 3: Decode the chromosome of each individual in the population and determine the fuzzy systems for sub-models. Evaluate the determined fuzzy systems by (6) and give a fitness value to each individual in the population by (7).

Step 4: Evolve a new population by reproduction, crossover, and mutation.

Step 5: Increase the generation number by one, and replace the old generation with the new one. During the replacement, preserve an individual that has the maximum fitness value by the elitist reproduction.

Step 6: Repeat Steps 3 through 5 until one of the following is satisfied:

(1) the satisfactory population shows up,

(2) the generation number reaches the maximum generation number, or

(3) the fitness function value is not increased for the predetermined generations.

Finally, the proposed IIE is summarized as Fig. 3.

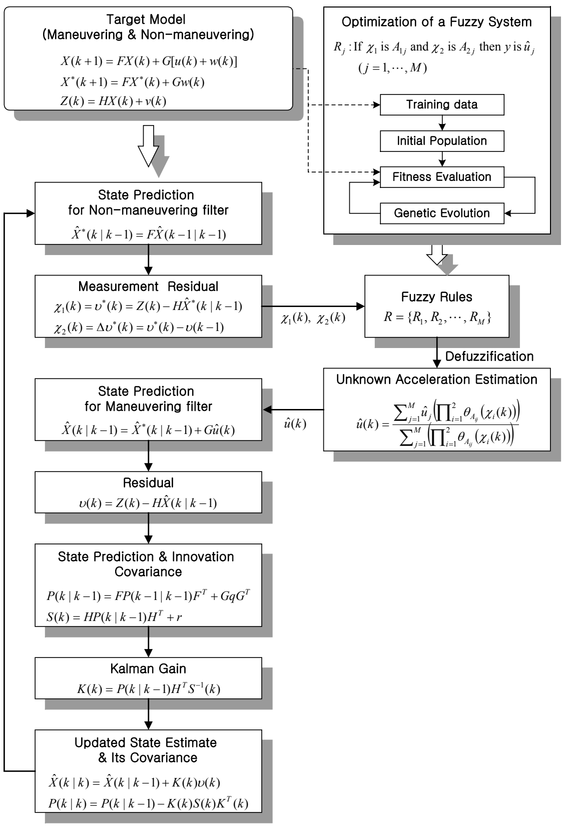


Fig. 3 Configuration of IIE

3.2 IMM method using IIE

The algorithm of the proposed IMM method using IIE follows.

Interaction of the estimates (mixing)

$$\hat{X}_{0m}(k-1|k-1)=\sum_{n=1}^{N}\mu_{n|m}(k-1|k-1)\hat{X}_n(k-1|k-1) \quad (8.1)$$

$$P_{0m}(k-1|k-1)=\sum_{n=1}^{N}\mu_{n|m}(k-1|k-1)\Big\{P_n(k-1|k-1) + [\hat{X}_n(k-1|k-1)-\hat{X}_{0m}(k-1|k-1)]\bullet [\hat{X}_n(k-1|k-1)-\hat{X}_{0m}(k-1|k-1)]^T\Big\} \quad (8.2)$$

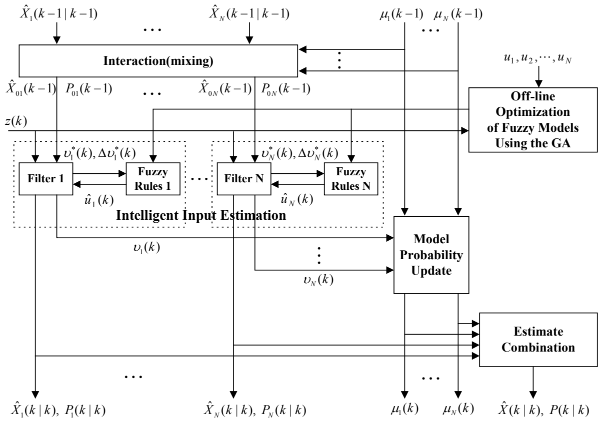


Fig. 4 IMM method using IIE

where the mixing probability $\mu_{n|m}$ and the normalization constant α_m are

$$\mu_{n|m}(k-1|k-1)=\frac{1}{\alpha_m}\phi_{nm}\mu_n(k-1) \quad (9.1)$$

$$\alpha_m=\sum_{n=1}^{N}\phi_{nm}\mu_n(k-1) \quad (9.2)$$

where ϕ_{nm} is the known model transition probability from the n th sub-model to the m th sub-model and $\mu_n(k-1)$ is the model probability of the n th sub-model at scan $k-1$.

Filtering algorithm

$$\hat{X}_m^*(k|k-1)=F\hat{X}_{0m}(k-1|k-1) \quad (10.1)$$

$$\chi_1(k)=\upsilon_m^*(k)=Z(k)-H\hat{X}_m^*(k|k-1) \quad (10.2)$$

$$\chi_2(k)=\Delta\upsilon_m^*(k)=\upsilon_m^*(k)-\upsilon_m(k-1) \quad (10.3)$$

$$\hat{u}_m(k)=\frac{\sum_{j=1}^{M}\hat{u}_j\left(\prod_{i=1}^{2}\theta_{A_{ij}}(\chi_i(k))\right)}{\sum_{j=1}^{M}\left(\prod_{i=1}^{2}\theta_{A_{ij}}(\chi_i(k))\right)} \quad (10.4)$$

$$\hat{X}_m(k|k-1)=\hat{X}_m^*(k|k-1)+G\hat{u}_m(k) \quad (10.5)$$

$$\upsilon_m(k)=Z(k)-H\hat{X}_m(k|k-1) \quad (10.6)$$

$$P_m(k|k-1)=FP_{0m}(k-1|k-1)F^T+GqG^T \quad (10.7)$$

$$S_m(k)=HP_m(k|k-1)H^T+r \quad (10.8)$$

$$K_m(k)=P_m(k|k-1)H^TS_m^{-1}(k) \quad (10.9)$$

$$\hat{X}_m(k|k)=\hat{X}_m(k|k-1)+K_m(k)\upsilon_m(k) \quad (10.10)$$

$$P_m(k|k)=P_m(k|k-1)-K_m(k)S_m(k)K_m^T(k) \quad (10.11)$$

Update of model probability

· likelihood function:

$$\Lambda_m(k)=\mathcal{N}[\upsilon_m(k);0,S_m(k)] =\frac{1}{\sqrt{2\pi|S_m(k)|}}\exp\left(-\frac{1}{2}\upsilon_m^T(k)S_m^{-1}(k)\upsilon_m(k)\right) \quad (11.1)$$

· model probability update:

$$\mu_m(k)=\frac{\Lambda_m(k)\alpha_m}{\sum_{n=1}^{N}\Lambda_n(k)\alpha_n} \quad (11.2)$$

Estimate combination

· state estimate:

$$\hat{X}(k|k) = \sum_{m=1}^{N} \mu_m(k)\hat{X}_m(k|k) \quad (12.1)$$

· estimate covariance matrix:

$$P(k|k) = \sum_{m=1}^{N} \mu_m(k)\{P_m(k|k) + [\hat{X}_m(k|k) - \hat{X}(k|k)][\hat{X}_m(k|k) - \hat{X}(k|k)]^T\} \quad (12.2)$$

Figure 4 describes the IMM method using IIE.

4. SIMULATION RESULTS

In this section, the simulations are divided in two parts: a simulation for searching the optimal fuzzy rules off-line and a simulation for tracking a maneuvering target. The tracking performance of the proposed method is compared with those of the IE technique and the AIMM method.

Table 1 The initial parameters of the GA

Parameters	Values
Maximum Generation	300
Maximum Rule Number	50
Population Size	500
Crossover Rate	0.9
Mutation Rate	0.01
λ	0.95

The initial parameters of the GA are presented in Table 1. The maximum acceleration input for whole simulations is assumed to be 0.1 km/s^2. The fuzzy rules identified off-line for the acceleration input $-0.01 < u_1(k) < 0.01$ (km/s^2) are showed in Table 2, for $0.01 \le u_2(k) \le 0.1$ (km/s^2) in Table 3, and for $-0.1 \le u_3(k) \le -0.01$ (km/s^2) in Table 4.

Table 2 Fuzzy rules identified for $u_1(k)$

No. of rule	Parameters identified for $-0.01 < u_1(k) < 0.01$ (km/s^2)				
	c_1	σ_1	c_2	σ_2	$\hat{u}$
1	0.229	0.707	1.205	2.483	0.0088
2	0.116	1.838	1.236	0.707	-0.0085
3	0.746	0.028	1.488	2.199	-0.0003
4	1.684	0.968	1.625	2.189	0.0018
5	1.459	0.661	-1.233	0.062	0.0081
6	-0.189	0.977	-0.626	0.249	-0.0094

Table 3 Fuzzy rules identified for $u_2(k)$

No. of rule	Parameters identified for $0.01 \le u_2(k) \le 0.1$ (km/s^2)				
	c_1	σ_1	c_2	σ_2	$\hat{u}$
1	-0.010	0.585	1.367	0.065	0.0302
2	0.972	0.046	0.999	1.781	0.0419
3	0.636	0.104	1.435	0.470	0.0106
4	0.277	1.829	1.092	1.017	0.0264
5	1.464	0.746	1.517	1.669	0.0524
6	-0.162	0.839	-1.087	1.104	0.0123
7	0.162	1.162	-0.428	1.955	0.0557
8	0.833	1.099	-0.963	0.471	0.0152
9	-0.212	0.016	-0.382	0.376	0.0585

Table 4 Fuzzy rules identified for $u_3(k)$

No. of rule	Parameters identified for $-0.1 \le u_3(k) \le -0.01$ (km/s^2)				
	c_1	σ_1	c_2	σ_2	$\hat{u}$
1	2.778	1.121	-0.638	1.124	-0.0530
2	0.941	1.486	1.259	0.306	-0.0471
3	0.879	1.739	0.919	0.612	-0.0402
4	2.065	0.558	1.633	1.875	-0.0289
5	1.137	1.279	1.763	1.943	-0.0221
6	0.895	0.240	1.452	2.693	-0.0477
7	-2.085	0.829	-0.652	2.908	-0.0172
8	-0.263	0.336	-0.736	2.098	-0.0396
9	1.596	3.252	0.203	0.229	-0.0279

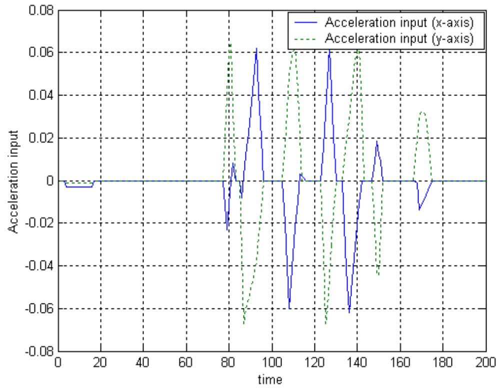


Fig. 5 Acceleration inputs (km/s^2)

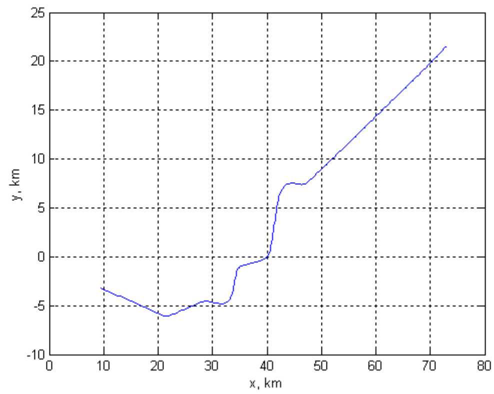


Fig. 6 Ideal motion of incoming anti-ship missile

The target is assumed as an incoming anti-ship missile on $x-y$ plane [13]. The initial position of the target is at [72.9 km 21.5 km], and it moves with a constant velocity of 0.3 km/s along a -150° line to the x-axis. The target has the lateral maneuvers as shown in Fig. 5, and the corresponding target motion is illustrated in Fig. 6. For both axes, the standard deviation of the zero mean white Gaussian measurement noise is 0.5 km and that of a random acceleration noise is 0.001 km/s^2. The standard deviations of the bias filter and the bias-free filter for a two-stage Kalman estimator are 0.01 km/s^2 and 0.001 km/s^2, respectively. The switching probability matrix of the sub-model, ϕ_{nm}, is taken by

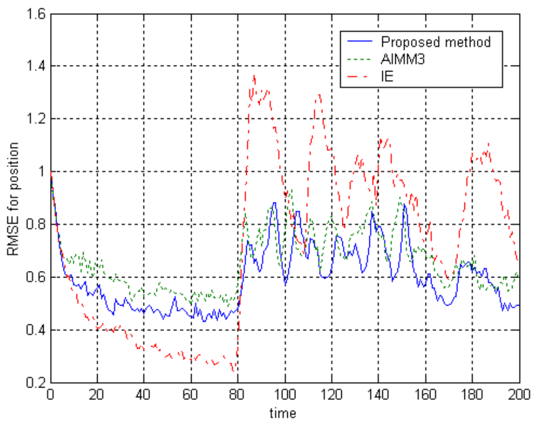
$$\phi_{nm} = \begin{cases} 0.97 & \text{if} \quad n = m \\ \dfrac{1 - 0.97}{N - 1} & \text{otherwise} \end{cases} \tag{13}$$

where N means the number of sub-models. Assuming that the first sub-model is nearer the motion model of the target, the initial model probability for sub-models is selected by

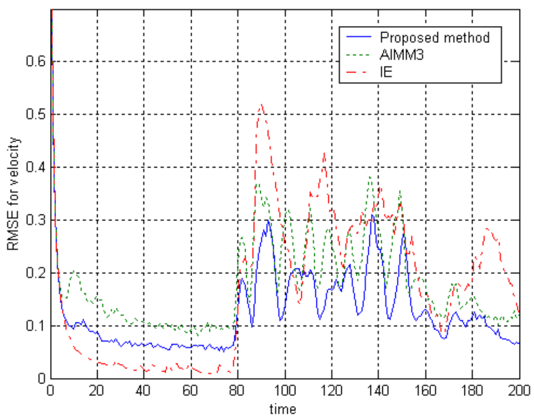
$$\mu_m(0) = \begin{cases} 0.6 & \text{if} \quad m = 1 \\ \dfrac{0.4}{N - 1} & \text{otherwise} \end{cases}. \tag{14}$$

The acceleration level of the sub-model for the AIMM3 (the AIMM method with 3 sub-models) method is 0.04 (km/s^2).

The simulation results and the numerical results over 100 runs are shown in Fig. 7.



a. RMSE for position



b. RMSE for velocity

Fig. 7 The simulation results

5. CONCLUSIONS

In this paper, we have proposed the IMM method using IIE for maneuvering target tracking. In the proposed method, the acceleration level for each sub-model was determined by IIE-the estimation of the unknown acceleration input by a fuzzy system using the relation between maneuvering filter residual and non-maneuvering one. The GA was utilized to optimize a fuzzy system for a sub-model within a fixed range of acceleration input. Then, multiple models were composed of these fuzzy systems, which were optimized for different ranges of acceleration input. In computer simulation for an incoming ballistic missile, we could obtain superior tracking performance compared with the IE technique and the AIMM method. Additionally, we could overcome the mathematical limits of the conventional multiple model methods.

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REFERENCES

[1] R. A. Singer, “Estimating optimal tracking filter performance for manned maneuvering targets,” *IEEE Trans. Aerosp. Electron. Syst.*, Vol. AES-6, No. 4, pp. 473–483, July, 1970.

[2] P. L. Bogler, “Tracking a maneuvering target using input estimation,” *IEEE Trans. Aerosp. Electron. Syst.*, Vol. AES-23, No. 3, pp. 298–310, May, 1987.

[3] Y. Bar-Shalom and K. Birmiwal, “Variable dimension filter for maneuvering target tracking,” *IEEE Trans. Aerosp. Electron. Syst.*, Vol. AES-18, No. 5, pp. 621–629, September, 1982.

[4] H. A. P. Blom and Y. Bar-Shalom, “The interacting multiple model algorithm for systems with a jump-linear smoothing application”, *IEEE Trans. Autom. Control*, Vol. AC-33, No. 8, pp. 780-783, August, 1988.

[5] A. Munir and D. P. Atherton, “Adaptive interacting multiple model algorithm for tracking a maneuvering target,” *IEE Proc. of Radar, Sonar, and Navigation*, Vol. 142, No. 1, pp. 11–17, 1995.

[6] A. T. Alouani, A. T. Xia, P. Price, and W. D. Blair, “A two-stage Kalman estimator for state estimation in the presence of random bias for tracking maneuvering targets,” *Proceedings of 30th IEEE Conference on Decision and Control*, pp. 2059–2062, December, 1991.

[7] L. X. Wang, *A Course in Fuzzy Systems and Control*, Prentice Hall, 1998.

[8] Y. Bar-Shalom and X. Li, *Estimation and Tracking; Principles, Techniques and Software*, Norwood, MA: Arteck House, 1993.

[9] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley, 1989.

[10] Y. H. Joo, H. S. Hwang, K. B. Kim, and K. B. Woo, “Linguistic model identification for fuzzy system,” *Electron. Letter*, Vol. 31, pp. 330–331, 1995.

[11] Y. H. Joo, H. S. Hwang, K. B. Kim, and K. B. Woo, “Fuzzy system modeling and its application to mobile robot control,” *Fuzzy Logic and its Applications to Engineering, Information Sciences, and Intelligent Systems*, ed. Z. Bien and K. C. Min, Kluwer Academic Publisher, pp. 147–156, 1995.

[12] Y. H. Joo, H. S. Hwang, K. B. Kim, and K. B. Woo, “Fuzzy system modeling by fuzzy partition and GA hybrid schemes,” *Fuzzy Sets and Systems*, Vol. 86, pp. 279–288, 1997.

[13] S. McGinnity and G. W. Irwin, “Fuzzy logic approach to maneuvering target tracking,” *IEE Proc. of Radar, Sonar, and Navigation*, Vol. 145, No. 6, pp. 337–341, 1998.