기동표적 추적을 위한 유전 알고리즘 기반 지능형 입력추정을 이용한 상호작용 다중모델 기법

IMM Method Using GA-Based Intelligent Input Estimation for Maneuvering target Tracking

이범직, 주영훈*, 박진배

연세대학교 전기전자공학과, *군산대학교 전자정보공학부

ABSTRACT

A new interacting multiple model (IMM) method using genetic algorithm (GA)-based 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 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.

Key words: IMM method, GA, IIE, maneuvering target tracking, fuzzy system

I. 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. 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 genetic algorithm (GA)-based 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 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 Simulations, the tracking performance of the proposed method is compared with those of the input estimation (IE) technique and the AIMM method.

II. Target Model

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

$$X(k+1) = FX(k) + G[u(k) + w(k)] \quad (1)$$

$$X(k+1) = FX(k) + Gw(k) \quad (2)$$

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

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

$$Z(k) = HX(k) + v(k) \quad (3)$$

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.

III. IMM Method Using GA-Based Intelligent Input Estimation

3.1. GA-Based IIE

In this paper, 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 [8], 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 [9]. Obviously the fuzzy system should be designed such that the difference between the actual acceleration input and the estimated one is minimized.

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

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.

3.2. Proposed method

The algorithm of the proposed IMM method using IIE follows.

Interaction of the estimates (mixing)

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

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

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

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

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

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

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

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

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

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

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

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

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

$$S_m(k) = HP_m(k \mid k-1)H^T + r$$

$$K_m(k) = P_m(k \mid k-1)H^T S_m^{-1}(k)$$

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

$$P_m(k \mid k) = P_m(k \mid k-1) - K_m(k)S_m(k)K_m^T(k)$$

Update of model probability

- likelihood function:

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

- model probability update:

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

Estimate combination

- state estimate:

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

- estimate covariance matrix:

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

Figure 1 describes the IMM method using IIE.

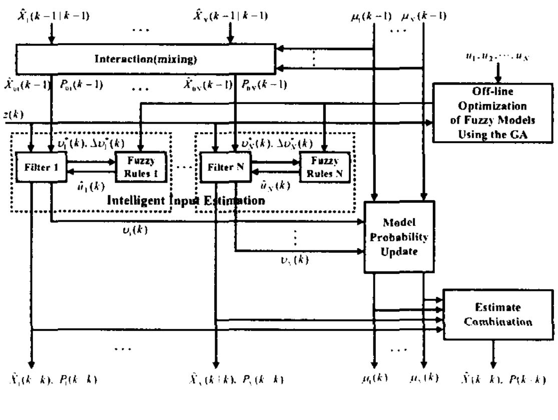


Fig. 1 IMM method using IIE

IV. 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.

The initial parameters of the GA are presented in Table 1. The maximum acceleration input for whole simulations is assumed to be $0.1\ km/s^2$.

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 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. 2, and the corresponding target motion is illustrated in Fig. 3.

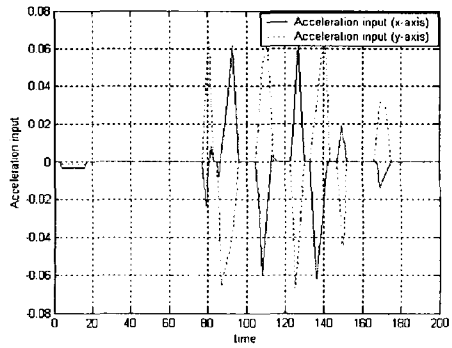


Fig. 2 Acceleration inputs (km/s^2)

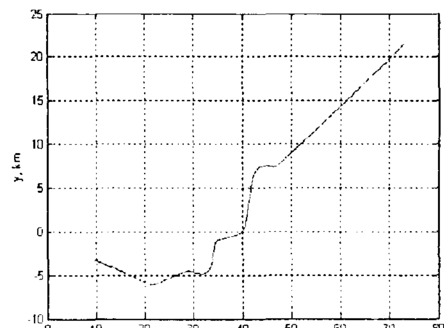
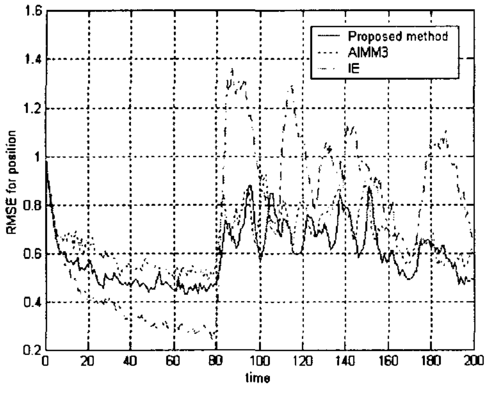
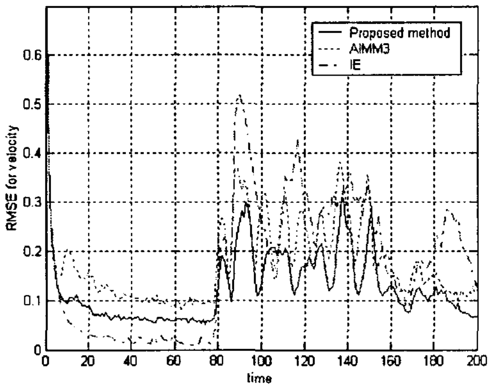


Fig. 3 Ideal motion of incoming anti-ship missile

The simulation results and the numerical results over 100 runs are shown in Fig. 4.



a. RMSE for position



b. RMSE for velocity

Fig. 4 The simulation results

V. Conclusions

In this paper, we have proposed the GA-based 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.

Acknowledgement

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

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

[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 by fuzzy partition and GA hybrid schemes," *Fuzzy Sets and Systems*, Vol. 86, pp. 279–288, 1997.

[12] 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.