퍼지 게인을 갖는 칼만필터를 이용한 IMM 기법

IMM Method Using Kalman Filter with Fuzzy Gain

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Abstract

In this paper, we propose an interacting multiple model (IMM) method using intelligent tracking filter with fuzzy gain to reduce tracking errors for maneuvering targets. In the proposed filter, to exactly estimate for each sub-model, we propose the fuzzy gain based on the relation between the filter residual and its variation. To optimize each fuzzy system, we utilize the genetic algorithm (GA). Finally, the tracking performance of the proposed method is compared with those of the adaptive interacting multiple model(AIMM) method and input estimation (IE) method through computer simulations.

Key word: Interacting multiple model, Maneuvering target tracking, Intelligent tracking filter, Fuzzy system, Genetic algorithm

1. 서 론

The design of a Kalman filter relies on having an exact dynamic model of the system under consideration in order to provide optimal performance. The accurate modelling of a maneuvering target is one of the most important problems when the Kalman filter is used for target tracking. However, there exists a mismatch between the modelled target dynamics and the actual target dynamics. If the system model of a maneuvering target is not correct, tracking loss will occur easily. These problems have been studied in the field of state estimation. Later, the various techniques were investigated and applied[1-2]. The interesting one of them is the interacting multiple model (IMM) approach[3]. In the algorithm, a parallel bank of filters are blended in a weighted-sum form by an underlying finite-dimensional Markov chain so that a smooth transition between sub-models is achieved. However, to realize a target tracker with an outstanding performance, a prior statistical knowledge on the maneuvering target should be supplied, i.e., the process noise variance for each sub-model in IMM should be accurately selected in advance by the domain expert who should fully understand the unknown maneuvering characteristics of the target, which is not an easy task.

An approach to resolve this problem is the adaptive interacting multiple model (AIMM) algorithm, where the acceleration is estimated via the two-stage Kalman filter and the model is selected based on the estimated acceleration[4]. However, in the method, the acceleration levels to construct the multiple models should also be predesigned in a trial and error manner, which significantly affect the tracking performance of the maneuvering target. Another important problem is that there is no direct measurement of acceleration available. As usual, significant delay and error arise in estimating acceleration from the noisy measurement of the position and the velocity.

Motivated by the above observations, we propose an intelligent tracking filter with fuzzy gain to reduce the additional effort required in conventional methods. The algorithm improves the tracking performance and establishes the systematic tracker design procedure for a maneuvering target. The complete solution can be divided into two stages. First, when the target maneuver occurs, the acceleration level for each sub-model is determined from the reference [5]. Second, to modify the accurate estimation, the target with maneuver is updated by using the fuzzy gain based on the fuzzy model. Since it is hard to approximate adaptively this time-varying variance and fuzzy gain owing to the highly nonlinear, a fuzzy system is applied as the universal approximator to compute it. To optimize each fuzzy system, we utilize the genetic algorithm (GA). On the other hand, the GA has shown to be a flexible and robust optimization tool for many nonlinear optimization problems, where the relationship between adjustable parameters and the resulting objective functions. Then, multiple models are represented as the acceleration levels estimated by these fuzzy systems, which are optimized for different ranges of acceleration input. Finally, the tracking performance of the proposed method is compared with those of the input estimation(IE) algorithm method and the IMM algorithm method through computer simulations.

2. Target model and IMM

The linear discrete time model for a maneuvering target and a non-maneuvering target are described for each axis as

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \tag{1}$$

$$x^{*k} = Ax_{k-1} + w_{k-1} \tag{2}$$

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

where, x_k is the state vector, the position and velocity of target, T is the time sampling, u_{k-1} is unknown maneuver input and w_{k-1} is the process noise, and zero mean white known covariance Q.

The measurement equation is

$$z_k = H_k x_k + v_k \tag{3}$$

where, $H = [1\,0]^T$ is the measurement matrix, and v_k is the measurement noise, and zero mean white known covariance R_k. Both Q_k and R_k are assumed to be uncorrelated..

3. Desing of IMM algorithm with fuzzy gain

When the target maneuver occurs in (1), the standard Kalman filter may not track the maneuvering target because the original process noise variance Q cannot cover the acceleration. The fuzzy systems to approximate $\hat{u}_k$ is shown in reference in [5] According to the Kalman filter, the predicted state of the target with maneuver can be written as

$$\hat{x}_{k|k-1} = \hat{x}^*_{k|k-1} + B\hat{u}_{k-1} + w \tag{4}$$

One cycle of the proposed IMM algorithm is summarized as follows: The mixed state estimate $\hat{x}^{0m}_{k-1|k-1}$ and its error covariance $P^{0m}_{k-1|k-1}$ are computed from the state estimates and their error covariances of sub-filters as follows:

$$\hat{x}^{0m}_{k-1|k-1} = \sum_{n=1}^{N} \mu^{n|m}_{k-1|k-1} \hat{x}^{n}_{k-1|k-1} \tag{5}$$

$$P^{0m}_{k-1|k-1} = \sum_{n=1}^{N} \mu^{n|m}_{k-1|k-1} \Big[P^{n}_{k-1|k-1} + \left(\hat{x}^{n}_{k-1|k-1} - \hat{x}^{0m}_{k-1|k-1}\right) \cdot \left(\hat{x}^{n}_{k-1|k-1} - \hat{x}^{0m}_{k-1|k-1}\right)^T \Big] \tag{6}$$

where the mixing probability $\mu^{n|m}$ and the normalization constant α^m are

$$\mu^{n|m}_{k-1|k-1} = \frac{1}{\alpha^m} \phi^{nm} \mu^{n}_{k-1} \tag{7}$$

$$\alpha^m = \sum_{n=1}^{N} \phi^{nm} \mu^{n}_{k-1} \tag{8}$$

Each sub-model provides the model state estimate update using the estimated acceleration $\hat{u}^m_k$ from $\hat{x}^{0m}_{k-1|k-1}$. and $P^{0m}_{k-1|k-1}$ are used as inputs to the sub-filter matched to the m sub-model to compute $\hat{x}^m_{k|k}$ and $\hat{P}^m_{k|k}$.

$$\hat{x}^{m*}_{k|k-1} = A\hat{x}^{0m}_{k|k} \quad (9)$$

$$\hat{u}^m_k = \frac{\sum_{j=1}^{M}\hat{u}_j\left(\prod_{i=1}^{2}\mu^{m_{ij}}(x_{ij})\right)}{\sum_{j=1}^{M}\left(\prod_{i=1}^{2}\mu^{m_{ij}}(x_{ik})\right)} \quad (10)$$

Because of the modified maneuver state $\hat{x}^m_{k|k-1}$, the measurement residual is defined. The modified fuzzy Kalman filter is corrected by the new update equation method. This filter is implemented by

$$\hat{z}^m_{k|k-1} = H_k\hat{x}^m_{k|k-1} \quad (11)$$

The residual of the estimation is defined as:

$$\tilde{z}^m_k = z^m_k - \hat{z}^m \quad (12)$$

Consider a double-input single-output fuzzy system with the linguistic rules.

$$Rule\ j: IF\ x_1\ is\ A_{1j}\ \text{and}\ x_2\ is\ A_{2j},\ THEN\ y\ is\ \bar{\gamma}_j \quad (13)$$

where two input x_1 and x_2 are the filter residual and change rate of the filter residual, respectively, and consequent variable y is the fuzzy correction gain γ_j, $A_{ij}(i \in 1,2$ and $j \in 1,2,...,M)$ is fuzzy set, it has the Gaussian membership function.

That is, we assume that the fuzzy system and we are going to design of the following form.

$$\bar{\gamma}_j = \frac{\sum_{j=1}^{M}\gamma_j\left(\prod_{i=1}^{2}\phi_{ij}(x_{ij})\right)}{\sum_{j=1}^{M}\left(\prod_{i=1}^{2}\phi_{ij}(x_i)\right)} \quad (14)$$

According to the approximation theorem by the GA, the fuzzy gain γ_k is optimized. The first measurement fuzzy gain is defined as

$$\gamma^F_k = [\bar{\gamma}_k\ \ \bar{\gamma}_k]^T \quad (15)$$

So, the state estimator under the fuzzy correction gain is then written as

$$\hat{x}^{Fm}_{k|k-1} = \hat{x}^m_{k|k-1} + \gamma^{Fm}_k \quad (16)$$

In the second stage, the measurement correction is the Kalman gain. The new update equation of the proposed filter can be modified as follows:

$$\begin{aligned}\hat{x}_{k|k} &= \hat{x}^{Fm}_{k|k-1} + K^m_k\left(z^{m_k} - H_k\hat{x}^{Fm}_{k|k-1}\right) \quad (17)\\ &= \hat{x}^m_{k|k-1} + \gamma^{Fm_k} + K^m_k\left[z^{m_k} - H_k(\hat{x}^m_{k|k-1} + \gamma^{Fm}_k)\right]\\ &= \left(I - K^m_k H_k\right)\left(\hat{x}^m_{k|k-1} + \gamma^{Fm}_k\right) + K^m_k z^m_k\end{aligned}$$

At the same time, the covariance matrix

$$P^m_{k|k} = P^m_{k|k-1} - K^m_k S^m_k K^{mT}_k \quad (18)$$

The innovation covariance is defined as

$$S^m_k = HP^m_{k|k-1}H^T + R \quad (19)$$

Secondly, the measurement correction is the Kalman gain. We can find the optimal Kalman filter gain.

$$K^m_k = P^m_{k|k}H^T S^{-m}_k \quad (20)$$

To approximate the unknown acceleration input $\hat{u}^m_k$ and the fuzzy gain γ^m_k, the GA is applied to optimize the parameters in both the premise and the consequence parts. The target tracker is to minimize the error, the fuzzy system should be designed such that the following objective function can be minimized:

$$\sqrt{(\sum position\ \ error)^2 + (\sum velocity\ \ error^2)} \quad (21)$$

Since the GA guides the optimal solution for the purpose of maximizing the fitness function value, it is necessary no map the objective function to the fitness function form by

$$f = \lambda\frac{1}{error+1} + (1-\lambda)\frac{1}{rule+1} \quad (22)$$

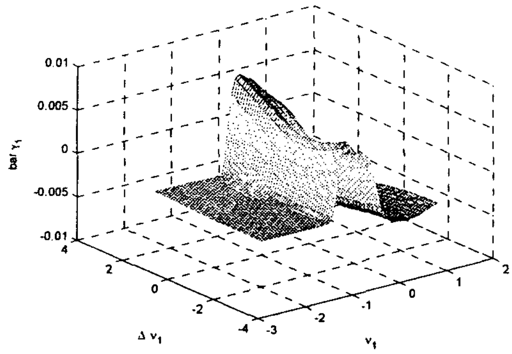
where λ is a positive scalar which adjusts the weight between the objective function and the rule number. Each individual is evaluated by a fitness function.

4. Simulation Results

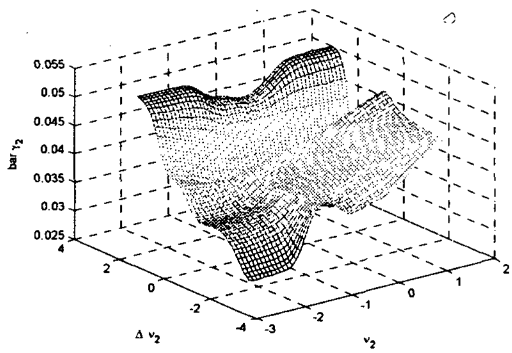
To evaluate the proposed filtering scheme, a maneuvering target scenario was examined and the theoretical analysis from the previous section show how to determined and updated for the maneuvering target model. For comparison purposes, we also simulated conventional the input estimation method (IE) and the adaptive interacting multiple method (AIMM) methods. We assumed that the target moves in a plane and its dynamics is given by (1). For convenience, the maximum target acceleration is assumed to be $0.1km/s^2$, and the sampling period T is $1s$. The fuzzy identified off-line for the acceleration input with the fuzzy gain $-0.01 < u^1_k < 0.01km/s^2$, $0.01 < u^2_k < 0.1km/s^2$, and for $-0.1 < u^3_k < 0.01km/s^2$ in Fig1. The initial position of the target is assumed to be $x_0 = 72.9km$, $y_0 = 3.0km$, and its velocity components are assumed to be $0.3km/s$ along the $-150°$ line to the $x-axis$. The standard deviation of the zero mean white Gaussian measurement noise is $R = 0.5^2$ and that of the random acceleration noise is $Q = 0.001^2$.

The standard deviations of the bias filter, and the bias-free filter for the two-stage Kalman estimator are $0.01km/s^2$ and $0.001km/s^2$, respectively, which are used only for the AIMM algorithm.

The simulation results with 100 Monte-Carlo simulations shown in Fig 2. Fig2 shows that the simulation results of the proposed method are compared with those of the IE method and AIMM.



(a) fuzzy gain1($-0.01 < u_k^1 < 0.01km/s^2$)



(b) fuzzy gain2 ($0.01 < u_k^2 < 0.1km/s^2$)

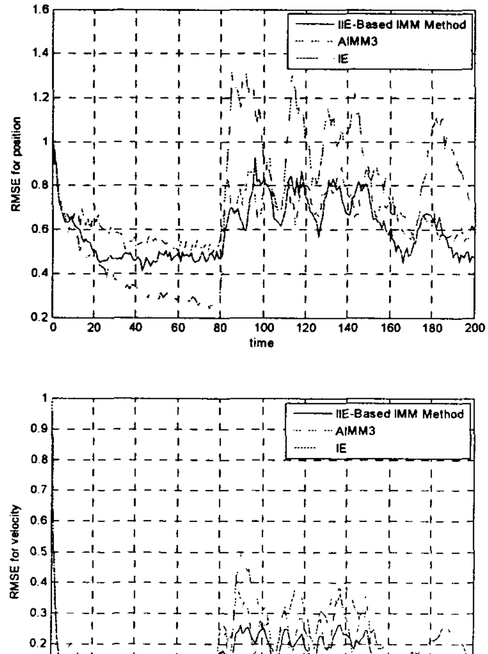
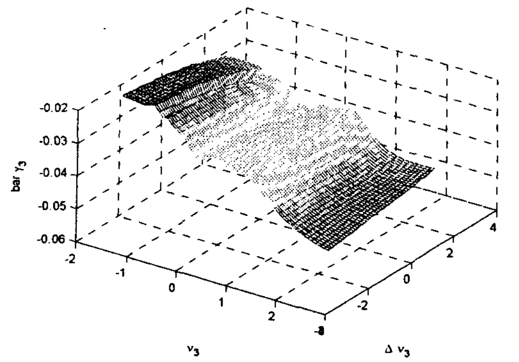


Fig.2 The results of position and velocity error



(c) fuzzy gain3 $-0.1 < u_k^3 < 0.01km/s^2$

Fig.1 The functional relationships of the fuzzy gain optimized for(a)

5. Conclusions

In this paper, we have developed IMM tracking algorithm with fuzzy gian. In the proposed method, the each sub-model is corrected by the proposed update equation method which is a fuzzy system using the relation between the filter residual and its variation. The GA was utilized to optimize a fuzzy system. In computer simulation, we have shown the proposed filter can effectively treat a target maneuver.

6. 참고문헌

[1] Y. Bar-Shalom and X. Li, *Estimation and Tracking: Principles, Techniques and Software*, Artech House, 1993.

[2] M. S. Grewal and A. P. Andrews, *Kalman filtering: theory and practice*, Prentice Hall, 1993.

[3] P. L. Bogler, "Tracking a maneuvering target using input estimation," *IEEE Trans. on Aerospace and Electronic Systems*, Vol. AES-23, No. 3, pp. 298-310, 1987.

[4] A. Munir and D. P. Atherton, "Adaptive interacting multiple model algorithm for tracking a maneuvering target, " *IEE Proc. of Radar., Sonar Navigation*, Vol. 142, No. 1, pp.

[5] B. J. Lee, Y. H. Joo, and J. B. Park, "IMM method using intelligent input estimation for maneuvering target tracking," *ICCA2003* pp. 1278-1282.