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기동 표적 추적을 위한 GA 기반 IMM 방법

GA-Based IMM Method Using Fuzzy Logic for Tracking a Maneuvering Target

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ABSTRACT

The accuracy in maneuvering target tracking using multiple models is caused by the suitability of each target motion model to be used. The interacting multiple model (IMM) algorithm and the adaptive IMM algorithm require the predefined sub-models and the predetermined acceleration intervals, respectively, in consideration of the properties of maneuvers to construct multiple models. In this paper, to solve these problems intelligently, a genetic algorithm (GA) based-IMM method using fuzzy logic is proposed. In the proposed method, a sub-model is represented as a set of fuzzy rules to model the time-varying variances of the process noises of a new piecewise constant white acceleration model, and the GA is applied to identify this fuzzy model. The proposed method is compared with the AIMM algorithm in simulations.

1. Introduction

The problem of tracking a maneuvering target has been studied in the field of the state estimation over decades. The Kalman filter has been widely used to estimate the state of the target, but in the presence of a maneuver, its performance may be seriously degraded. The recent researches to track a maneuvering target are roughly divided in two main approaches[1-5]. One is to detect a maneuver and to cope with it effectively, and the other is to describe the motion of the target with multiple models. In this paper, the second approach is mainly discussed.

The accuracy in maneuvering target tracking using multiple models is caused by the suitability of each target motion model to be used for a maneuver. In the IMM algorithm, the estimate is obtained by a weighted sum of the estimates from sub-models in accordance with the probability of each model being effective[3]. But, in order to construct multiple models, this algorithm requires the predefined sub-models with different dimensions or different process noise levels in consideration of the properties of maneuvers. On the other hand, the adaptive IMM (AIMM) algorithm does not need the predefined sub-models because of estimating the acceleration of the target adaptively and constructing multiple models by using this estimated acceleration[4]. However, the acceleration intervals, which are symmetrically added in or subtracted from the estimated acceleration value to construct multiple models, should also be determined by the properties of maneuvers.

In this paper, in order to solve these problems intelligently and track a maneuvering target effectively, the GA based-IMM method using fuzzy logic is proposed. In the maneuvering target model, the constant acceleration input during some periods is regarded as an additive noise. In the proposed method, a sub-model is represented as a set of fuzzy rules to model the time-varying variances of the process noises. In order to identify the parameters and the structure of this fuzzy model for a certain maneuver input within the assumed maximum acceleration input, the GA is applied. Then, multiple models are composed of these fuzzy models, which are identified for various maneuvers.

2. Previous Works

The linear discrete time model for a maneuvering target is described for each axis by

$$x(k+1)=Fx(k)+G\{u(k)+w(k)\}$$

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

where $x(k)=[\xi\ \ \dot{\xi}]^T$ 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 deterministic acceleration input.

The measurement equation is

$$z(k)=Hx(k)+v(k)$$

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, respectively, and the correlation of them is assumed to be zero

The AIMM algorithm 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 estimated one.

In the AIMM algorithm, the acceleration of the target is estimated in parallel for each axis by a two-stage Kalman estimator, which consists of bias-free filter and bias filter. The bias filter equations to estimate the acceleration of the target are as follows[5]:

$$\hat{a}(k|k-1)=\hat{a}(k-1|k-1)$$
$$P^a(k|k-1)=P^a(k-1|k-1)+Q^a$$
$$S(k)=HU(k-1)$$
$$V(k)=(I-K(k)H)U(k)$$
$$U(k)=FV(k-1)+G$$
$$K^a(k)=P^a(k|k-1)S^T(k)\cdot[S(k)P^a(k|k-1)S^T(k)+HP(k|k-1)H^T+R]^{-1}$$
$$\hat{a}(k|k)=\hat{a}(k|k-1)+K^a(k)[r(k)-S(k)\hat{a}(k|k-1)]$$
$$P^a(k|k)=[I-K^a(k)S(k)]P^a(k|k-1)$$

where $\hat{a}(k|k)$ is the bias vector, $P^a(k)$ is the covariance of the bias, Q^a is the process noise for the bias vector, $U(k)$ and $V(k)$ are the sensitivity matrices, $K^a(k)$ is the Kalman gain of the bias filter, and $S(k)$, $K(k)$ and $r(k)$ are obtained from the bias-free filter.

The AIMM algorithms to be represented by the acceleration which is estimated from the two-stage Kalman estimator are as follows[4]:

Interaction of the estimates (mixing)

$$\hat{x}_{0j}(k-1|k-1)=\sum_{i=1}^{r}\mu_{i|j}(k-1|k-1)\,\hat{x}_i(k-1|k-1)$$

$$P_{0j}(k-1|k-1)=\sum_{i=1}^{r}\mu_{i|j}(k-1|k-1)\{P_i(k-1|k-1)+[\hat{x}_i(k-1|k-1)-\hat{x}_{0j}(k-1|k-1)]\cdot[\hat{x}_i(k-1|k-1)-\hat{x}_{0j}(k-1|k-1)]^T$$

where the mixing probability $\mu_{i|j}$ is

$$\mu_{i|j}(k-1|k-1)=p_{ij}\mu_i(k-1)/\sum_{i=1}^{r}p_{ij}\mu_i(k-1)$$

where p_{ij} is the known mode transition probability.

Filtering algorithm

$$\hat{x}_j(k|k-1)=F\hat{x}_{0j}(k-1|k-1)+G\hat{a}_j(k-1)$$
$$P_j(k|k-1)=FP_{0j}(k-1|k-1)F^T+GqG^T$$
$$\hat{z}_j(k|k-1)=H\hat{x}_j(k|k-1)$$
$$S_j(k)=HP_j(k|k-1)H^T+R$$
$$K_j(k)=P_j(k|k-1)H^TS_j^{-1}(k)$$
$$\hat{x}_j(k|k)=\hat{x}_j(k|k-1)+K_j(k)[z(k)-\hat{z}_j(k|k-1)]$$
$$P_j(k|k)=P_j(k|k-1)-K_j(k)S_j(k)K_j^T(k)$$

Mode probability update

$$\mu_j(k)=\Lambda_j(k)\sum_{i=1}^{r}p_{ij}\mu_i(k-1)/\sum_{j=1}^{r}\Lambda_j(k)\sum_{i=1}^{r}p_{ij}\mu_i(k-1)$$

where the likelihood function Λ_j is

$$\Lambda_j(k)=\aleph[r_j(k);0,S_j(k)]=\frac{1}{\sqrt{(2\pi)^m|S_j(k)|}}\exp\left(-\frac{1}{2}r_j^T(k)S_j(k)r_j(k)\right)$$

Estimate combination

$$\hat{x}(k|k)=\sum_{j=1}^{r}\mu_j(k)\,\hat{x}_j(k|k)$$

$$P(k|k)=\sum_{j=1}^{r}\mu_j(k)\{P_j(k|k)+[\hat{x}_j(k|k)-\hat{x}(k|k)]\cdot[\hat{x}_j(k|k)-\hat{x}(k|k)]^T$$

3. GA-Based IMM Method

In the maneuvering target model, the constant acceleration input during some periods, $u(k)$, is regarded as an additive noise, and each sub-model is expressed by a new piecewise constant white acceleration model with time-varying variances of the process noises. A new piecewise constant white acceleration model is

$$x(k+1)=Fx(k)+Gw^*(k)$$

where $w^*(k)$ is the zero-mean white Gaussian noise sequence with the time-varying variance of the process noise $q^*(k)$. In this method, a sub-model is represented as a set of fuzzy rules to model the time-varying variances of the process noises of this new model by using the relation among the residuals, their variations and the time-varying variances of the process noises for a certain acceleration input. In order to identify the parameters and the structure of this fuzzy model, the GA is applied. Multiple models for tracking a maneuvering target are finally composed of these fuzzy models which are identified for various maneuvers. The proposed method is illustrated by Figure 1.

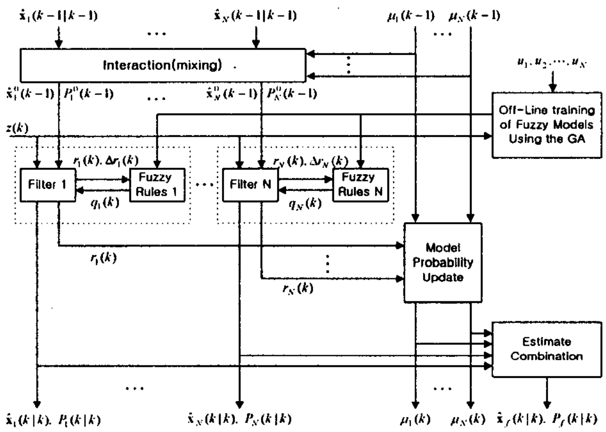


Fig. 1 The GA based IMM method

The j-th fuzzy inference rule with scatter-partitioned structure within the range of the input or the output space is represented by

rule j : If x_1 is A_1^j and x_2 is A_2^j, then y is w^j

where two input variables, x_1 and x_2, are the residual $r(k)$ and its variation $\Delta r(k)$ of a new piecewise constant white acceleration model, respectively, an output variable y is the time-varying variance $q_j^*(k)$ of the process noise for rule j, w^j is a real value, and

A_i^j is the Gaussian membership function with the following membership grade $\mu_i^j(x_i)$.

$$\mu_i^j(x_i)=\exp\left[-\frac{1}{2}\left(\frac{x_i-c_i^j}{\sigma_i^j}\right)^2\right]$$

where, c_i^j and σ_i^j are the center value and the standard deviation of Gaussian membership function for i-th input variable of j-th rule, respectively.

In this paper, the GA is used to identify the premise and the consequent parameters of a fuzzy model and its rule number[9]. The GA is the method to obtain an optimal solution based on the principles of natural population genetics and natural selection although the mathematical relationship between the parameter to be identified and the nonlinear function to be optimized is not known exactly.

The genetic coding is the way in which a fuzzy rule is represented as a chromosome. Fuzzy modeling using the GA is started from the genetic coding and in the process of genetic coding the potential solutions in given problem play an important role in the performance of the GA. The proposed genetic coding method is illustrated in Figure 2. In this coding method, the parameter string and the rule number string are used to optimize the premise and consequent parameters and the number of fuzzy rules, respectively. The parameter string consists of the premise string and the consequent string. The premise string consists of the center values c_i^j and the standard deviations σ_i^j of Gaussian membership function, and the consequent string is chosen as the real value w^j. The rule number string is coded as the binary string by assigning 1 for the valid rules and 0 for the invalid rules.

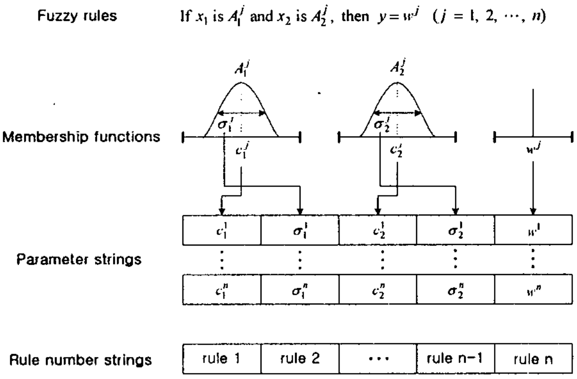


Fig. 2 The proposed genetic coding method

Initial population is made up with initial individuals to the extent of the population size. The premise string of each initial individual is determined at random within the range of residual $r(k)$ and the range of variation of residual $\Delta r(k)$, and the corresponding consequent string is determined at random by using the possible range of the standard deviation of the process noise as follows[6]:

$$0.5(a_M+\sqrt{q})\le\sigma^*(k)\le(a_M+\sqrt{q})$$

where $\sigma^*(k)$ is the standard deviation of the process noise and a_M is the maximum value of the acceleration input.

Each individual is evaluated by the following fitness function. The fitness of an individual is determined in inverse proportion to the error and the number of rules.

$$fitness=\lambda\frac{1}{error+1}+(1-\lambda)\frac{1}{rule\ number+1}$$

where λ means the relative value between the error and the rule number, and error is defined by

$$error=\sqrt{(\Sigma position\ error)^2+(\Sigma velocity\ error)^2}$$

4. Simulation Results

In this section, the performance of the proposed method is compared with that of the AIMM algorithm. The initial parameters of the GA are presented in Table 1. It is assumed that the maximum acceleration input for whole simulations is $0.1\,km/s^2$. The fuzzy rules for each sub-model are identified off-line for the acceleration input $u_1=0.001km/s^2$, $u_2=0.01km/s^2$ and $u_3=0.1km/s^2$.

Table 1 The initial parameters of the GA

Parameters	Value
Maximum Generation	100
Maximum Rule Number	50
Population Size	500
Crossover Rate	0.9
Mutation Rate	0.01
λ	0.95

The initial position of the target in $x-y$ plane is at $22.4\,km$ along a 45° line to x-axis, and it moves with a constant velocity of $0.015\,km/s$ along a 45° line to x-axis. The target motion according to acceleration inputs for each axis is described in Figure 3.

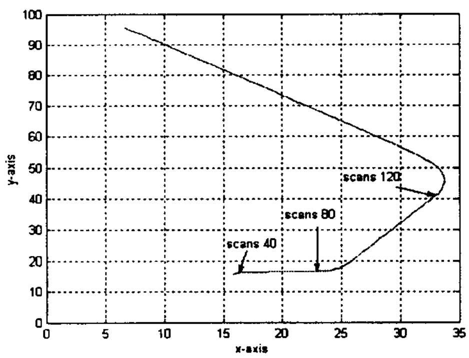


Fig. 3 The target motion

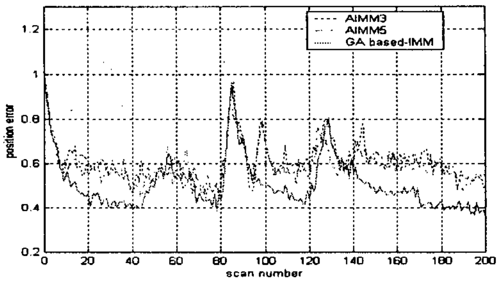
For both axes, the standard deviation of the zero mean white Gaussian measurement noise is $0.5\,km$ and that of a random acceleration noise is $0.001\,km/s^2$. The standard deviations of the bias filter and the bias-free filter for a two-stage Kalman estimator are $0.01\,km/s^2$ and $0.001\,km/s^2$, respectively. The switching probability matrix and the initial model probability for the sub-model was taken by

$$P_{ij}=\begin{cases} 0.97 & \text{if } i=j \\ \dfrac{1-0.97}{N-1} & \textit{otherwise} \end{cases}$$

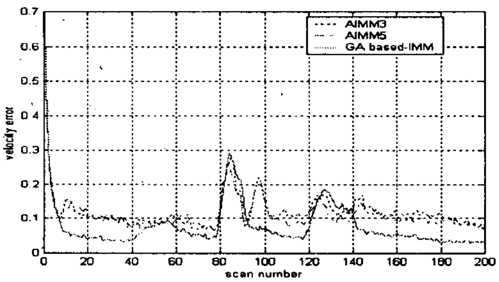
$$w_i=\begin{cases} 0.6 & \text{if } i=1 \\ \dfrac{1-0.6}{N-1} & \textit{otherwise} \end{cases}$$

In the AIMM algorithm, the acceleration levels of sub-models are 0.04 for AIMM3 with 3 sub-models, and 0.02 and 0.04 for AIMM5 with 5 sub-models.

The simulation results and numerical results over 100 Monte Carlo runs are shown in Figure 4 and in Table 2, respectively.



a. Position error



b. Velocity error

Fig. 4 The simulation result

Table 2 The numerical results

Configuration	No. of sub-models	Error/Scan	
		Position	Velocity
AIMM3	3	0.6089	0.1235
AIMM5	5	0.6003	0.1176
GA-based IMM	3	0.5107	0.0818

5. Conclusions

In this paper, we have developed the GA based-IMM method using fuzzy logic for tracking a maneuvering target. In the proposed method, a sub-model was represented as a set of fuzzy rules to model the time-varying variances of the process noises of a new piecewise constant white acceleration model and the GA was applied for identifying this fuzzy model for a certain deterministic maneuver input. Multiple models were then composed of these fuzzy models. The proposed method hasthree advantages in comparison with the IMM algorithm or the AIMM algorithm. Firstly, unlike an IMM algorithm, the sub-models predefined in consideration of the property of maneuver are not required. Secondly, unlike an AIMM algorithm, the estimation of the target acceleration and the adjustment for different acceleration levels in accordance with the property of maneuver are not required in order to construct sub-models. Thirdly, although the property of maneuver is unknown, the proposed method can be applied if the maneuver is within the assumed maximum acceleration input. The simulation results with two scenarios have shown that the proposed method had the better tracking performance in comparison with the AIMM algorithm.

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