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기동 표적 추적을 위한 유전알고리즘 기반 퍼지 모델링 기법

노선영[*], 이범직[**], 주영훈[***], 박진배[*]
*연세대학교 전기공학과, **국방과학연구소, *** 군산대학교 전자정보공학부

GA based fuzzy modeling method for tracking a maneuvering target

Sun Young Noh[*], Bum Jik Lee[**], Young Hoon Joo[***], and Jin Bae park[*]
*Yonsei Univ. **A.D.D., ***Kunsan National Univ.

Abstract - This paper proposes the genetic algorithm (GA)-based fuzzy modeling method for intelligent tracking of a maneuvering target. When the maneuvering to turn or taking evasive action, the performance of the standard Kalman filter has been degraded because residual between the modeled target dynamics and the actual target dynamics. To solve this problem, the state prediction error is minimized by the intelligent estimation method. Then, this filter is corrected by measurement corrections which is the fuzzy system. The performance of the proposed method is compared with those of the input estimation(IE) technique through computer simulation.

1. Introduction

The standard Kalman filter show good performance for target tracking with a linear dynamic model, but its performance is rapidly degraded in case of high maneuvering and nonlinear dynamic targets. This problem has been studied in the field of state estimation over decades. Development of an accurate system model requires maneuver detection and estimation of the magnitude of maneuver. Usually it is not impossible to detect the exact onset time of maneuver. To solve this problem, various techniques have been investigated and applied. Singer proposed a target tracking model in which maneuver was assumed as a random process with known exponential autocorrelation [1]. Since the Singer's method, The input estimation technique for tracking a maneuvering target is proposed by Chan et al [2]. In this method, the magnitude of the acceleration is identified by the least-squares estimation when a maneuver is detected. Then the estimated acceleration is used in conjunction with a standard Kalman filter to compensate the state estimate of the target. However, the difference in the assumed and the actual maneuver onset time eventually increases the tracking errors after a target starts to maneuver and its method lead to large tracking errors during the target maneuvering model [3]. To solve this problem and decrease the tracking error effectively, we propose the GA-based fuzzy modeling method in this paper. In the maneuvering target model, the state prediction error is determined by the intelligent estimation method that means the acceleration input using the relation between maneuvering filter residual and non-maneuvering one. The genetic algorithm(GA) is utilized to optimize a fuzzy system. Then, this filter is corrected by measurement corrections which is the fuzzy system. In section 2 of this paper, we describe the maneuvering target model and standard Kalman filter, and the details of the proposed method are described in Section 3. In section 4, the tracking performance of the input estimation technique. Conclusion is provided in Section 5.

2. Preliminaries

2.1 Maneuvering target model

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

$$x(k+1) = Fx(k) + Gu(k) + v(k) \tag{1}$$

$$F = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \qquad G = \begin{bmatrix} T/2 \\ T \end{bmatrix} \tag{2}$$

where $x(k) = [x \quad \dot{x} \quad y \quad \dot{y}]^T$ is the state vector, the position and velocity of target, T is the time sampling, $u(k)$ is maneuver input and $v(k)$ is the process noise, and zero mean white Gaussian noise with known covariance Q.

The measurement equation is

$$z(k) = Hx(k) + w(k) \tag{3}$$

where $H = [1 \ 0]^T$ is the measurement matrix, $w(k)$ is the measurement noise, and zero mean white known covariance R. Both $v(k)$ and $w(k)$ are assumed to be uncorrelated.

2.2 The standard Kalman filter algorithm

The standard Kalman filter estimates a process by using a form of feedback control. This filter estimates the process state at some time and then obtains feedback in the form of measurements. As such, the equation for the Kalman filter fall into two groups. First prediction equations as follows:

$$\hat{x}(k+1|k) = F\hat{x}(k) + Gu(k) + v(k) \tag{4}$$

$$P(k+1|k) = FP_x(k|k)F^T + Q(k) \tag{5}$$

$$\hat{z}(k+1|k) = H\hat{x}(k+1|k) \tag{6}$$

Second, the measurement update equations are responsible for the feed back.

$$\hat{x}(k+1|k+1) = F\hat{x}(k+1|k) + K[z(k) - H\hat{x}(k+1|k)] \tag{7}$$

$$P(k+1|k+1) = (I - KH)P(k) \tag{8}$$

$$K(k+1) = P_x(k+1|k)H^T S^{-1}(k+1) \tag{9}$$

where $\hat{x}(k)$, $\hat{z}(k)$, K and $P(k)$ represent the estimated state, the estimated measurement, Kalman gain matrix, and the estimation error covariance matrix, respectively.

3. GA-Based fuzzy modeling method

3.1 GA-based input estimation method

In this section, in order to improve that tracking performance, the proposed method is the off-line optimization of a fuzzy system. The acceleration input is determined by a fuzzy system using the relation between acceleration residual and its variation for the maneuvering target.

R_l : If χ_1 is A_{1j} and $\chi_2(k)$ is A_{2j}, then y is u_j

where $x_1(k)$ and $x_2(k)$ are acceleration residual and its variation, and $u_j(k)$ is the state prediction error.
The Gaussian membership A_{ij} with the c_{ij} and the standard deviation σ_{ij} has the following membership grade.

$$\theta_{A_{ij}}(x_i) = \exp\left(-\frac{(x_i - c_{ij})^2}{2(\sigma_{ij})^2} \right) \tag{10}$$

By using singleton fuzzifier, product inference and center-average defuzzifier $u_j(k)$ can be estimated in the following form.

$$u(k) = \frac{\sum_{l=1}^{M} u_j \left(\prod_{i=1}^{2} \theta_{A_{ij}}(x_i(k)) \right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{2} \theta_{A_{ij}}(x_i(k)) \right)} \tag{11}$$

We utilize the GA, in order to optimize the parameters in both the premise part and the consequence part of the fuzzy system simultaneously. The optimization process is performed for the direction of minimizing the tracking errors.

The GA represents the searching variables of the given optimization problem as a chromosome containing one or more sub-string. 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 u_j. A convenient way to convey the searching variables into the chromosome is to gather all searching variables associated with the jth fuzzy rule into a string and to concatenate the strings as

$$S_j = \{c_{1j}, \sigma_{1j}, c_{2j}, \sigma_{2j}, q_j\},$$
$$S = \{S_1, S_2, \ldots, S_M\}$$

where S_j is the real coded parameter substring of the jth 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. We define the state prediction error $\tilde{u}$ and its covariance P as :

$$P = E(\tilde{u}\tilde{u}^T) \tag{12}$$

where $E(\cdot)$ is the expected value operator. We can find the minimizing covariance by the proposed method.

3.2 Measurement correction method

In this subsection, we use the fuzzy system and the optimized filter which is state prediction of maneuvering filter is implemented by fuzzy correction gain. Its design step can be defined as follows.
At first, the measurement residual is defined by

$$\tilde{z}_{error}(k+1) = z(k+1) - H\hat{x}(k+1|k) \tag{13}$$

And, then the fuzzy correction gain is defined by

$$F_{cg}(k+1) = FC\left[\tilde{z}_{error}(k+1)\right] \tag{14}$$

where $FC(\cdot)$ presents the functional characteristics of the fuzzy linguistic decision scheme, which in the present study is based on the linguistic rules of the form.

$R_j(j=1,\cdots,7)$: If χ_1 is A_{1j}, then y_j is B_{1j}

where A_i and B_i denote the linguistic term sets such as negative big(NB), negative medium(NM), zero(ZR), positive medium(PM), and positive big(PB), which are represented as fuzzy subsets of the universe of discourse that corresponds to the domain of the variable of interest.
The decision making rules can be implemented as $\mu^j_{F_{cg}}(k+1) = \mu^j_z(k+1)$, where $\mu^j_{F_{cg}}$ is the membership value of the fuzzy gain with respect to each fuzzy subset. The defuzzification strategy is realized as

$$F_{cg}(k+1) = \frac{\sum \mu^j_{F_{cg}}(k+1)c_j}{\sum \mu^j_{F_{cg}}(k+1)} \tag{15}$$

where c_j is the mean value for centroid defuzzification method.
The fuzzy logic correction array for the tracking problem becomes

$$F_{cgay}(k+1) = \begin{bmatrix} 0 \\ F_{cg}(k+1) \end{bmatrix} \tag{16}$$

Then the measurement state update under the $FC(\cdot)$ is

$$\hat{x}_{FC}(k+1) = F\hat{x}(k+1|k) + F_{cgay}(k+1) \tag{17}$$

The second measurement correction is the Kalman gain correction and its associated updating equations of the state estimation and the estimation error covariance are defined by

$$\begin{aligned} \hat{x}(k+1|k+1) &= \hat{x}_{FC}(k+1|k) + K\left[z(k+1) - H\hat{x}_{FC}(k+1|k)\right] \\ &= \hat{x}(k+1|k) + K\left[z(k+1) - H\hat{x}_{FC}(k+1|k)\right] + \\ &\quad \left(F_{cgay}(k+1) - KHF_{cgay}(k+1)\right) \end{aligned} \tag{18}$$

$$P(k+1|k+1) = P(k+1|k) - KS(k)K^T \tag{19}$$

where the Kalman gain matrix is determined by

$$K = P(k+1|k)H^T[HP(k+1|k)H^T + R]^{-1}. \tag{20}$$

4. Simulation Results

In this subsection, the simulation studies were performed to compare the input estimation.

The target scenario is assumed as an incoming anti-ship missile on x-y plan [5]. The target starts from an initial position is at $[72.9km, 21.5km]$, and its a constant velocity is at $0.3km/s$ in a -150° line to the x-axis. For the x and y axes, the standard deviation of the zero mean white measurement noise is $0.5km$ and that of a random acceleration noise is $0.001km/s^2$. The sampling time T is $1s$. The lateral acceleration maneuvers starts at $80s$ and the corresponding target motion is illustrated in Fig.1

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

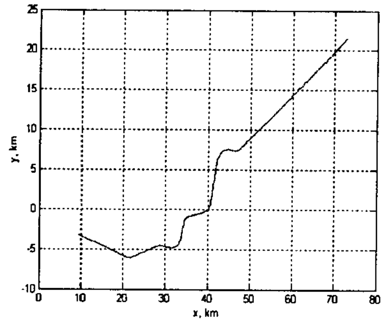


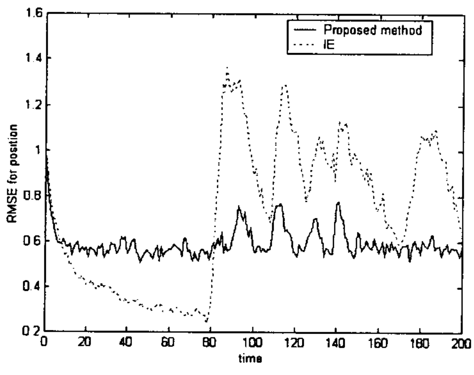
Fig. 1 Acceleration inputs (km/s^2)

Table 1 The initial parameters of the GA

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

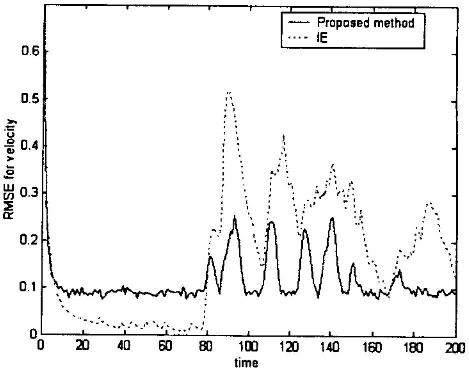
Table 2 The simulation results

Configurations	The results	
	ζ_p	ζ_v
IE	0.7252	0.1733
Proposed method	0.5921	0.1166



(a) Normalized position error

The simulation results over 100 runs are shown in Fig. 2, the proposed method had much better tracking performance than the IE algorithm.



(b) Normalized velocity error

Fig. 2 The simulation results

5. Conclusion

In this paper, we have developed the GA-based intelligent tracking method for a maneuvering target. In the proposed method, the state prediction error was determined by the intelligent estimation method, the covariance was minimized. Then, this filter was corrected by measurement corrections which was the fuzzy system. In computer simulation, we had much better tracking performance than the IE technique.

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