GA- ased Fu y Kalman Filter for Tracking the Maneuvering Target

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Abstract: This paper proposes the design methodology of genetic algorithm (GA)-based fuzzy Kalman filter for tracking the maneuvering target. The performance of the standard Kalman Filter (SKF) has been degraded because mismatches between the modeled target dynamics and the actual target dynamics. To solve this problem, we use the method to estimate the increment of acceleration by a fuzzy system using the relation between maneuver filter residual and non-maneuvering one. To optimize the fuzzy system, a genetic algorithm (GA) is utilized and this is then tuned by the fuzzy logic correction. Finally, the tracking performance of the proposed method has been compared with those of the input estimation (IE) technique and the intelligent input estimation (IIE) through computer simulations.

Keywords: Maneuvering target tracking, GA-based Fuzzy Kalman filter method, Fuzzy logic correction, Fuzzy system, Input estimation technique, intelligent input estimation.

1. INTRODUCTION

Modeling of the maneuvering target system accurately is one of the most important problems when using the Kalman filter for target tracking. This problem has been studied in the field of state estimation over decades. If the system model of a maneuvering target is not correct, track loss will occur easily. 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, a generalized likelihood ratio (GLR) was computed when the two hypotheses corresponded to the presence or absence of a maneuver [2]. A common method in the application uses non-maneuvering target model for tracking a target moving at a constant velocity and then switches to a tracking filter for an appropriate maneuvering model, when the target maneuver is detected.

The input estimation technique for tracking a maneuvering target is proposed by Chan et al [4]. 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 [3-5]. Furthermore, the filter uses the only measurements at the starting point of sliding window to initialize the augmented filter. These processes may increase the tracking error.

To solve this problem and decrease the tracking error effectively, we propose GA-based Fuzzy Kalman filter in this paper. In the maneuvering target model, the acceleration is determined by the intelligent input estimation (IIE) that 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 [7-8]. The genetic algorithm (GA) is utilized to optimize a fuzzy system. Then, this filter is implemented by two-stage measurement corrections which is the functional characteristics of the fuzzy linguistic decision scheme. Its method is using single-input single-output fuzzy model with 7 rules.

Section 2 of this paper describes maneuvering target model and summarizes the input estimation technique as previous works, and the details of the proposed method are described in Section 3. In Section 4, the tracking performance of the proposed method is compared with those of the input estimation technique and the intelligent input estimation (IIE) [8]. Conclusion is provided in Section 5.

2. PRELIMINARIES

2.1 Maneuvering target model

We assume that the target moves in a plane which is the two-dimensional case. The discrete time equation model for a maneuvering target and a non-maneuver are described for each axis by

$$x(k+1) = \quad x(k) + Gu(k) + v(k) \qquad (1)$$

$$x(k+1) = \quad x(k) + v(k) \qquad (2)$$

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

$$E \quad v(k) = 0 \qquad E \quad v(k)v^T(k) = Q$$

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

The measurement equation is

$$z(k) = Hx(k) + w(k) \qquad (3)$$

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

2.2 Input estimation techni ue

In this model, acceleration is treated as an additive input term in the system equation [6]. A Kalman filter consists of the hypothetical one based on the maneuvering model (1) and the actual one based on the non-maneuvering model (2). From the innovation of the non-maneuvering filter based on (2), the unknown acceleration $u(k)$ is to be detected, estimated, and compensated to correct the state estimate. For the convenience, the present time is denoted by k, and it is assumed that the target starts maneuvering at maneuver onset time $(k-s)$.

According to the Kalman filter, the predicted state of the target with maneuver at $(k-s)$ is

$$\hat{x}^*(i+1) = \quad [I - K(i)H]\hat{x}^*(i|i-1) + \quad K(i)z(i) \quad (4)$$

$$(i = k-s, ..., k-1)$$

where the mismatched non-maneuvering filter based on (2) will be denoted by an asterisk, k is the Kalman gain of the non-maneuvering filter and the initial condition is the correct estimate before the maneuver started

$$\hat{x}^*(k-1|k-s-1) = \hat{x}(k-1|k-s-1) \quad (5)$$

The solution of discrete time state equation (4) in terms of (5)

$$\hat{x}^*(i+1|i) = \left[{}_{j=0}^{j-k+s} \Phi(i-j) \right] \hat{x}(k-1|k-s-1) \quad (6)$$

$$+ {}_{j=k-s}^{i} \left[{}_{m=0}^{i-j-1} \Phi(i-m) \right] K(j)z(j)$$

The recursion for state estimation from the hypothetical correct filter based on (3) in the case of the known input is the following

$$\hat{x}(i+1|i) = \Phi(i)\hat{x}(i|i-1) + \quad K(i)z(i) + Gu(i) \quad (7)$$

$$= \left[{}_{j=0}^{j-k+s} \Phi(i-j) \right] \hat{x}(k-s|k-s-1)$$

$$+ {}_{j=k-s}^{i} \left[{}_{m=0}^{j-k-1} \Phi(i-m) \right] [\quad K(j)z(j) + Gu(j)]$$

The innovation of the correct filter, zero mean white sequence with covariance $S(i+1)$ are

$$v(i+1) = z(i+1) - H\hat{x}(i+1|i) \quad (8)$$

and the innovation corresponding to the non-maneuvering filter (4) are

$$v^*(i+1) = z(i+1) - H\hat{x}^*(i+1|i) \quad (9)$$

Then the estimated acceleration is used in conjunction with a standard Kalman filter to compensate the state estimate of the target. This method uses the only measurements at the starting point of sliding window to initialize the augmented filter. There processes may increases the tracking error.

3. T E GA- ASED FU KALMAN FILTER

3.1 The intelligent input estimation (IIE)

In this section, in order to improve the tracking performance, we propose the GA-based Fuzzy Kalman filter algorithm that is the off-line optimization of a fuzzy system. The acceleration is determined by the IIE [8]. The IIE means the estimation of the unknown acceleration input by a fuzzy system using the relation between maneuvering filter residual and non-maneuvering one.

For the Kalman filter with the maneuvering input (1), the residual of the estimation is defined as

$$\tilde{z}_{error}(k+1) = z(k+1) - H(\hat{x}(k+1)) \quad (10)$$

Acceleration term, in this model, is considered as an additive input to the system [5]. Accordingly, acceleration residual and its variation for the maneuvering target based on the maneuvering model (1) are

$${}_1(k) = z^*(k) = z(k) - \hat{z}\ (k) \quad (11)$$

$${}_2(k) = \quad z\ (k) = z\ (k) - z(k-1) \quad (12)$$

The unknown acceleration input $u_j(k)$ is inferred by a double-input single-input (DISO) fuzzy system, of which the j th fuzzy IF-THEN rule is represented

R_j : If ${}_1$ is A_{1j} and ${}_2(k)$ is A_{2j}, then y is u_j

where two premise variables $x_1(k)$ and $x_2(k)$ are the non-maneuvering filter residual $z^*(k)$ and the difference between non-maneuvering residual $z^*(k)$ and maneuvering filter residual $z(k-1)$, respectively. A consequence variable y is the estimated acceleration input $u_j(k)$. The Gaussian membership A_{ij} with the center c_{ij} and the standard deviation σ_{ij} has the following membership grade.

$${}_{A_{ij}}(x_i) = \exp \ -\frac{(x_i - c_{ij})^2}{2(\sigma_{ij})^2} \quad (13)$$

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

$$\hat{u}(k) = \frac{{}_{j=1}^{M} \hat{u}_j \left({}_{i=1}^{2}\ {}_{A_{ij}}(x_i(k)) \right)}{{}_{j=1}^{M} \left({}_{i=1}^{2}\ {}_{A_{ij}}(x_i(k)) \right)} \quad (14)$$

We utilize the GA, in this subsection, 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 to some acceleration levels within the possible range of the target acceleration [9].

Obviously the fuzzy system should be designed such that the difference between the actual acceleration input and the estimated one is minimized.

$$E = {}_{k=1} (u(k) - \hat{u}(k)) \quad (15)$$

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

$$S_j = \{c_{1j}, \sigma_{1j}, c_{2j}, \sigma_{2j}, q_j\},$$

$$S = \{S_1, S_2, ..., S_M\}$$

where S_j is the real coded parameter substring 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.

Fig. 1 illustrates the structure of the chromosome for the GA-based intelligent Kalman filter, where the initial population is made up with initial individuals to the extent of the population size.

Each individual is evaluated by a fitness function. Since the GA originally searches the optimal solution so that the fitness function value is maximized, mapping the objective function (16) to the fitness function is necessary. Furthermore, since it is strongly desired that we reduce the number of the fuzzy IF-THEN rules in a hardware implementation and a computation resource point of view is strongly desired, we use the fitness function of the form

$$f(J) = \frac{}{J+1} + \frac{1-}{M+1} \tag{16}$$

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

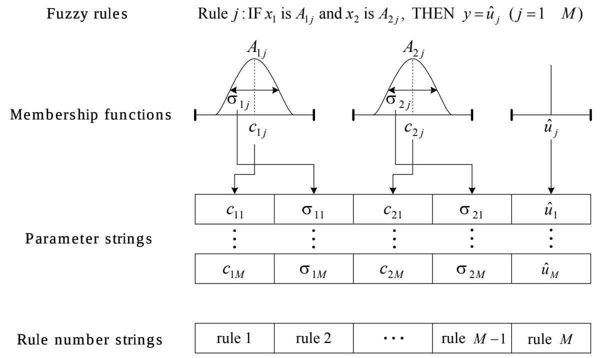


Fig. 1 Decision strings in a chromosome

3.2 Fu y logic correction method

In this subsection, we use the Takagi-Segno (T-S) fuzzy system and the optimized Fuzzy Kalman filter which is state prediction of maneuvering filter is implemented by tow-stages of measurement corrections. The first method of measurement correction is to define the measurement residual (10) and then the fuzzy correction gain is defined by

$$_{cg}(k+1) = \quad C\left[\tilde{z}_{error}(k+1)\right] \tag{17}$$

where FC(.) presents the functional characteristics of the fuzzy linguistic decision scheme.

Consider a single-input-single-output (SISO) fuzzy system with the linguistic rules.

R_j(j = 1, ,7) : If $_1$ is A_{1j}, then y_j is B_{1j}

where input variables, $_1$ is the filter residual $\tilde{z}_{error}(k+1)$ and a consequent variable y_j is the fuzzy correction gain $_{cg}(k+1)$ for the 7th fuzzy rule. The A_{ij} and B_{ij} are the membership function, in order for a fuzzy rule base to be complete, it must contain the following seven rules whose If parts constitute the linguistic term sets.

If $\tilde{z}_{error}$ is PB, Then is PB,

If $\tilde{z}_{error}$ is PM, Then is PM,

If $\tilde{z}_{error}$ is PS, Then is PS,

If $\tilde{z}_{error}$ is ZR, Then is ZR,

If $\tilde{z}_{error}$ is NS, Then is NS,

If $\tilde{z}_{error}$ is NM, Then is NM,

If $\tilde{z}_{error}$ is NB, Then is NB,

The Fig. 2 is shown the decision making rule.

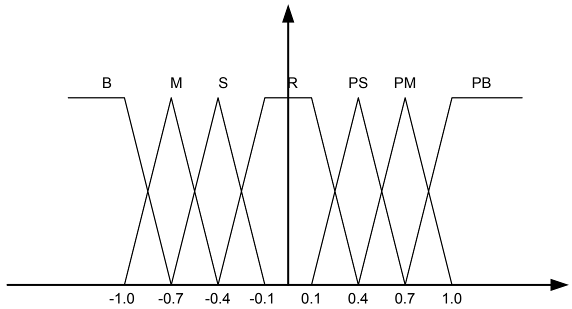


Fig. 2 The membership function for estimation error

The decision making rules can be implemented as $^{j}_{cg}(k+1) = \,^{j}_{\tilde{z}_{error}}(k+1)$, where $^{j}_{cg}$ is the membership value of the fuzzy gain with respect to each fuzzy subset. The defuzzification strategy is the following form.

$$_{cg}(k+1) = \frac{\sum_{j=1}^{7} \,^{j}_{cg}(k+1)c_j}{\sum_{j=1}^{7} \,^{j}_{cg}(k+1)} \tag{18}$$

where c_j is the mean value element of 1-level cut set with respect to each fuzzy subset.

The fuzzy logic correction array for the tracking problem becomes [10]

$$_{cgay}(k+1) = \begin{bmatrix} 0 \\ _{cg}(k+1) \end{bmatrix} \tag{19}$$

Then the measurement state update under the FC is

$$\hat{x}_C(k+1) = \quad \hat{x}(k+1|k) + \quad _{cgay}(k+1) \tag{20}$$

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

$$\begin{aligned} \hat{x}(k+1|k+1) &= \hat{x}_C(k+1|k) + K\left[z(k+1) - H\hat{x}_C(k+1|k)\right] \\ &= \hat{x}(k+1|k) + K\left[z(k+1) - H\hat{x}_C(k+1|k)\right] + \\ &\quad \left(_{cgay}(k+1) - KH \quad _{cgay}(k+1)\right) \end{aligned} \tag{21}$$

$$P(k+1|k+1) = P(k+1|k) - KS(k)K^T \tag{22}$$

where the Kalman gain matrix is determined by

$$K = p(k+1|k)H^T\left[Hp(k+1|k)H^T + R\right]^{-1} \tag{23}$$

This proposed method filtering algorithm can be replaced for the proposed GA-based Fuzzy Kalman filter method as follows.

$$\hat{x}(k+1|k) = \quad \hat{x}(k|k) \tag{24a}$$

$$_1(k) = z^*(k) = z(k) - \hat{z}\ (k) \tag{24b}$$

$$\hat{x}(k+1|k) = \hat{x}(k+1|k) + G\hat{u}(k) \tag{24c}$$

$$\tilde{z}_{error}(k+1) = z(k+1) - H(\hat{x}(k+1)) \tag{24d}$$

$$_{cg}(k+1) = \quad C\left[\tilde{z}_{error}(k+1)\right] \tag{24e}$$

$$S(k+1) = Hp(k+1|k)H^T + r \tag{24f}$$

$$P(k+1 \quad k) = \quad P(k \quad k) \quad ^T + GqG^T \tag{24g}$$

$$K(k+1) = P(k+1|k)H^T S^{-1}(k+1) \tag{24h}$$

$$\hat{x}(k+1|k+1) = \hat{x}_C(k+1|k) + K\left[z(k+1) - H\hat{x}_C(k+1|k)\right] \quad (24i)$$

$$P(k+1|k+1) = P(k+1|k) - KS(k)K^T \quad (24j)$$

The proposed method is illustrated in Fig. 3.

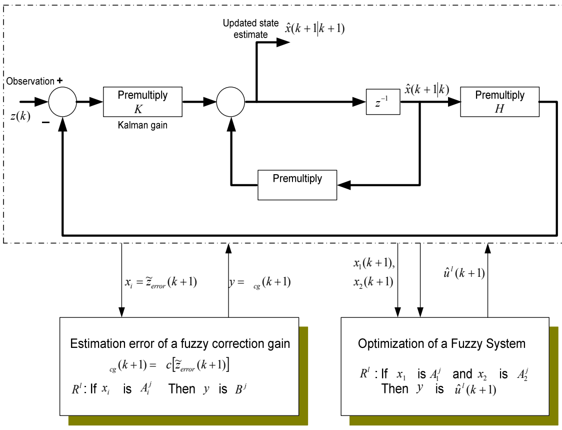


Fig. 3 GA-based Fu y Kalman filter algorithm

4. SIMULATION RESULTS

In this subsection, the simulation studies were performed to compare the input estimation and the proposed method. The target scenario is assumed as an incoming anti-ship missile on x-y plan [13]. 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 $0.001\,km/s^2$. The sampling time T is $1\,s$. In the Figure 4, the lateral acceleration maneuvers starts at 80 s and the corresponding target motion is illustrated in Fig. 5

The initial parameters of the GA are presented in Table 1.

The maximum acceleration in put for whole simulations is assumed to be $0.1km/s^2$. The fuzzy rules identified off-line for the acceleration in put $-0.01\quad u_1(k)\quad 0.01(km/s^2)$ are shoed in Table 2, for $0.01\quad u_2(k)\quad 0.1(km/s^2)$ in Table 3, and for $-0.1\quad u_3(k)\quad -0.01(km/s^2)$ in Table 4 [8].

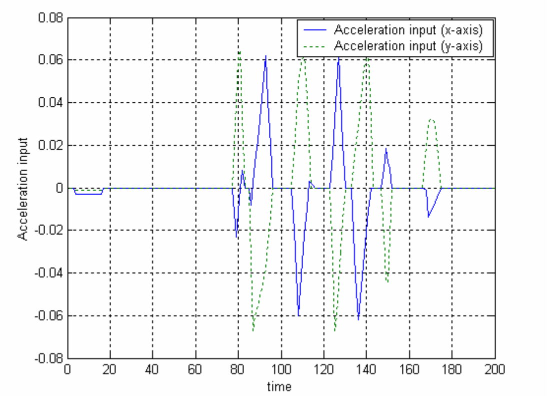


Fig. 4 Acceleration inputs (km/s^2)

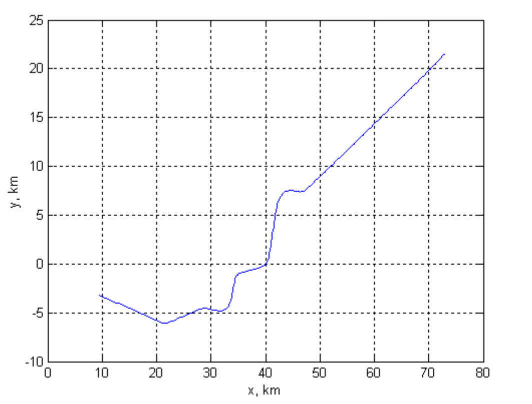


Fig. 5 The motion of incoming anti-ship missile

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
	0.95

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

No. of rule	Parameters identified for $-0.01\quad u_1(k)\quad 0.01\ (km/s^2)$				
	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 $u_2(k)$

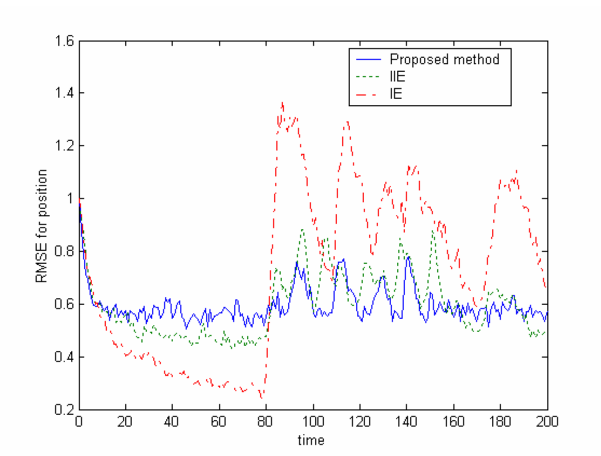
No. of rule	Parameters identified for $0.01\quad u_2(k)\quad 0.1\ (km/s^2)$				
	c_1	σ_1	c_2	σ_2	$\hat{u}$
1	-0.010	0.585	1.367	0.065	0.0302
2	0.972	0.046	0.999	1.781	0.0419
3	0.636	0.104	1.435	0.470	0.0106
4	0.277	1.829	1.092	1.017	0.0264
5	1.464	0.746	1.517	1.669	0.0524
6	-0.162	0.839	-1.087	1.104	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 $u_3(k)$

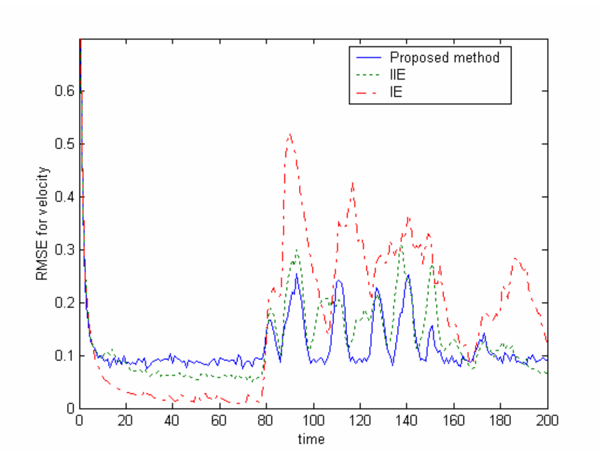
No. of rule	Parameters identified for $-0.1\quad u_3(k)\quad -0.01\ (km/s^2)$				
	c_1	σ_1	c_2	σ_2	$\hat{u}$
1	2.778	1.121	-0.638	1.124	-0.0530
2	0.941	1.486	1.259	0.306	-0.0471
3	0.879	1.739	0.919	0.612	-0.0402
4	2.065	0.558	1.633	1.875	-0.0289
5	1.137	1.279	1.763	1.943	-0.0221

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

The simulation results over 100 runs are shown in Fig. 7, the proposed method had much better tracking performance than the IIE algorithm and IE algorithm.



(a) Normali ed position error



(b) Normali ed velocity error

Fig. The simulation results

5. CONCLUSION

In this paper, we have developed the GA-based IIE method as an intelligent tracking method for a maneuver target. In the proposed method, the acceleration was determined by IIE method which is the estimation of the 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. Then, this filter is implemented by two-stage measurement corrections. In computer simulation, we had much better tracking performance than the IIE algorithm and IE algorithm.

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