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Design of Target Tracking System Using a New Intelligent Algorithm

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Abstract

When the maneuver occurs, the performance of the standard Kalman filter has been degraded because mismatches between the modeled target dynamics and the actual target dynamics. To solve this problem, the unknown acceleration is determined by using the fuzzy logic based on genetic algorithm(GA) method. This algorithm is the method to estimate the increment of acceleration by a fuzzy system using th relation between maneuver fitler residual and non-maneuvering one. To optimize this system, a GA is utilized. And then, the modified filter is corrected by the new update equation method which is a fuzzy system using the relation between the filter residual and its variation. To shows the feasibility of the suggested method with only one filter, the computer simulations system are provided, this method is compared with multiple model method.

Key words : Maneuvering target tracking, GA, fuzzy system,multiple model

1. Introduction

The most important problem when using the Kalman filter for target tracking is modeling method of the maneuvering target system. 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 [3]. 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 [4,5]. 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, we propose a new intelligent tracking algorithm to reduce the additional effort required in conventional methods, improve the tracking performance, and establish the systematic tracker design procedure for a maneuvering target. In this algorithm, the acceleration is determined by 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 [6,7]. And, because this algorithm used multiple models, its computational cost was very high. To solve these difficulties, we adopt the fuzzy correction gain using the new update equation method which is a fuzzy system using the relation between the filter residual and its variation. In addition, to optimize the fuzzy system employed within the range of practicable target acceleration, we utilize a GA and the gradient descent(GD) method is then applied to identify the fuzzy correction gain. Finally, the tracking performance of the proposed method is compared with those of an interacting multiple model(IMM) and adaptive interacting multiple model(AIMM) through computer simulations.

This paper is organized as follows: Section 2 of this paper describes maneuvering target model and non-maneuvering target model, 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 IMM method and AIMM method. Conclusion is provided in Section 5.

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2. Maneuvering target model

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

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (1)$$

$$x_k = Ax_{k-1} + w_{k-1} \quad (2)$$

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

$$E\langle w_k \geq 0 \quad E\langle w_k w_k^T \geq Q$$

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_{k-1}.

The measurement equation is

$$z_k = H_k x_k + v_k \quad (2)$$

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-1} and R_k are assumed to be uncorrelated..

3. The new intelligent estimation algorithm

3.1 The unknown input detection method

In this section, in order to decrease the tracking error, we propose the GA-based fuzzy Kalman filter algorithm. This algorithm is the estimation of the unknown acceleration input by a fuzzy system using the non-maneuvering filter residual v_k^* and the difference between non-maneuvering filter(1) residual v_k^* and maneuvering filter(2) residual v_{k-1}.

The unknown acceleration input u_{k-1} is inferred by fuzzy system, of which the jth fuzzy IF-THEN rule is represented.

$$Rule\, j: IF\, x_1\, is\, A_{1j} \text{ and } x_2\, is\, A_{2j},\ THEN\, y\, is\, u_j \quad (5)$$

where two premise variables x_1 and x_2 are the v_k^* and the $v_k^* - v_{k-1}$ respectively. A consequence variable y is the acceleration input u_j. The A_{ij} are fuzzy sets, and throughout this paper, it has the Gaussian membership function with the center c_{ij} and the standard deviation σ_{ij} as follows:

$$\mu_{ij}(x_i) = \exp\left[-\frac{1}{2}\left(\frac{x_i - c_{ij}}{\sigma_{ij}}\right)^2\right] \quad (5)$$

$\hat{u}_k$ is approximated in the following form:

$$\hat{u}_k = \frac{\sum_{j=1}^{M} u_j\left(\prod_{i=1}^{2}\mu_{ij}(x_{ij})\right)}{\sum_{j=1}^{M}\left(\prod_{i=1}^{2}\mu_{ij}(x_{ik})\right)} \quad (6)$$

To facilitate the fuzzy system to approximate $\hat{u}_k$ and ensure that the best possible set of rules be found, a GA is applied to the parameters in both premise and consequence part, and the number of rules simultaneously. In that case, we define that the searching variables are the center and the standard deviation for a Gaussian membership function of the fuzzy set and the singleton output. A convenient way to convey the searching variables into the chromosome is to gather all searching variables associated with the fuzzy rules into a string and to concatenate the strings.

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 to the fitness function is necessary. According to the universal approximation theorem[8], there exist optimal parameters which can approximate $\hat{u}_k$ as closely as possible.

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

$$E = \sum_k (u_k - \hat{u}_k) \quad (7)$$

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.

The GA that optimally estimates the unknown acceleration input in the proposed method is summarized as follows.

Step 1 : Set the initial parameters for the GA (maximum generation number, maximum rule number, population size, crossover rate, and mutation rate).

Step 2 : Randomly generate the initial population such that all search variable exist within the search space

Step 3 : Decode the chromosome of each individual in the population and determine the fuzzy systems. Evaluate the determined fuzzy systems using () and give a fitness value to each individual in the population using ().

Step 4 : Evolve a new population by reproduction, crossover, and mutation. In the GA, one-point crossover and point mutation operations are used.

Step 5 : Increase the generation number by one, and replace the old generation with the new one. During the replacement, preserve an individual who has the maximum fitness value by elitist reproduction.

Step 6 : Repeat Step 4 to 5 until one of the following is satisfied:
(1) a satisfactory population occurs;
(2) the generation number reaches a preset maximum value, or
(3) the fitness function value is not increased for the predetermined generations.

3.2 A new update equation method

In the preceding section, out primary concern was the detection of the unknown target maneuver. In this maneuver model, the system equation was firstly modified to unknown maneuver input . The modified fuzzy Kalman filter is corrected by the new update equation method. This filter is implemented by tow-stages of measurement corrections. The first stage for updating measurement is to defined the measurement residual and the fuzzy correction gain is then defined by the fuzzy system. The second state for updating measurement is the Kalman gain correction.

In the first stage, filter can be derived by assuming a recursive estimator of the form:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + B\hat{u}_{k-1} \tag{8}$$

We defined the state prediction covariance P using the estimate do the maneuver as:

$$P_{k|k-1} = AP_{k-1|k-1}F^T + GqG^T \tag{9}$$

The state measurement prediction of system can be rewritten as:

$$\hat{z}_{k|k-1} = H_k\hat{x}_{k|k-1} \tag{10}$$

The residual of the estimation by using the equation (10) and (2) is defined as:

$$\tilde{z}_k = z_k - \hat{z}_{k|k-1} \tag{11}$$

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

$$Rule\ j: IF\ x_1\ is\ A_{1j}\ \text{and}\ x_2\ is\ A_{2j},\ THEN\ y\ is\ \bar{\gamma}_j \tag{12}$$

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 $j\in 1,2,\dots,M)$ is fuzzy set, it has the Gaussian membership function.

In this paper, a gradient descent(GD) method is applied to optimize the parameters and the structure of the system. That is, we assume that the fuzzy system and we are going to design of the following form.

$$\overline{\gamma}_j = \frac{\sum_{j=1}^{M}\gamma_j\left(\prod_{i=1}^{2}\phi_{ij}(x_{ij})\right)}{\sum_{j=1}^{M}\left(\prod_{i=1}^{2}\phi_{ij}(x_i)\right)} \tag{13}$$

Consider an error function e^p given by

$$E_j \cong [\overline{\gamma}_j - \tilde{z}_k]$$
$$e^p = \frac{1}{2M}[\sum_{j=1}^{M}E_j^2] \tag{14}$$

By using (13), the state estimator is corrected. The first measurement correction is defined.

$$\gamma_{Fg_k} = [\bar{\gamma}_k\ \bar{\gamma}_k] \tag{15}$$

So, the state estimator under the fuzzy correction gain (15) is then written as

$$\hat{x}_{Fg_{k|k-1}} = \hat{x}_{k|k-1} + \gamma_{Fg_k} \tag{16}$$

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

$$\begin{aligned}\hat{x}_{k|k} &= \hat{x}_{Fg_{k|k-1}} + K_k(z_k - H_k\hat{x}_{Fg_{k|k-1}}) \\ &= \hat{x}_{k|k-1} + \gamma_{Fg_k} + K_k[z_k - H_k(\hat{x}_{k|k-1} + \gamma_{Fg_k})] \\ &= (I - K_kH_k)(\hat{x}_{k|k-1} + \gamma_{Fg_k}) + K_kz_k\end{aligned} \tag{17}$$

These modifications do not alter the basic computational sequence used in the standard Kalman filter. Therefore, the designed target tracking system gives satisfactory performance for diverse maneuvers.

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 interacting multiple method (IMM) and the adaptive interacting multiple method (AIMM) methods. We assumed that thetarget moves in a plane and its dynamics is given by (1). For convenience, the maximum target acceleration is assumed to be $0.1 km/s^2$, which is determined to sufficiently cover the target maneuver, and the sampling period T is $1s$. The initial parameters of the GA are presented in Table 1. The fuzzy rules identified off-line for the unknown acceleration input u_k are showed in Table 2.

Table 1. The initial parameters of the GA

Parameters	Values
Maximum Generation	200
Maximum Rule Number	50
Population Size	500
Crossover Rate	0.9
Mutation Rate	0.01
λ	0.75

The target is assumed to be an incoming anti-ship missile on the $x-y$ plane [9]. The initial position of the target is assumed to be $x_0=72.9$ km, $y_0=3.0$ km, and its velocity components are assumed to be 0.3km/s along the $-150°$ line to the $x-axis$. The target has lateral accelerations as shown in Fig. 1, and the corresponding target motion is illustrated in Fig. 2. The standard deviation of the zero mean white Gaussian measurement noise is $R=0.5^2$ and that of the random acceleration noise is $Q=0.001^2$. After the unknown target acceleration is determined, the modified filter is implemented by the measurement correction method. The gradient descent(GD) method is used to optimize the fuzzy membership function. Table 5 shows the training data that is used for the GD optimization.

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 model transition probability from the nth sub-model to the mth one for the IMM and AIMM methods are assumed to be

$$\Phi=\begin{cases} 0.97 & \text{if } n=m \\ \dfrac{1-0.97}{N-1} & otherwise \end{cases} \tag{18}$$

where N is the total number of sub-models. We further assume that the initial motion of the target is similar to that of the first sub-model, so the initial model probability for each sub-model is chosen as

$$\mu_m(0)=\begin{cases} 0.3 & \text{if } n=1 \\ \dfrac{1-0.6}{N-1} & otherwise \end{cases} \tag{19}$$

The simulation results with 100 Monte-Carlo simulations shown in Fig. 3 and Fig. 4. Fig. 3 shows that the simulation results of the proposed method are compared with those of the IMM method. Fig. 4 shows that the simulation results of the proposed method are compared with those of the AIMM.

Table 2. The fuzzy rules optimized by GA

Rules	c_1	σ_1	c_2	σ_2	q
1	-1.0878	0.33846	1.354	1.9143	0.25572
2	2.2674	0.5233	-0.34196	1.5641	0.32371
3	0.2969	0.23509	-0.75719	2.4434	0.268
4	1.1958	0.00296	0.54166	2.6425	0.57787
5	2.6621	0.17242	-0.7678	2.3292	0.41058
6	3.1437	1.3031	-0.8653	2.4755	0.98979
7	1.8006	0.45909	-0.752	0.00364	0.35309

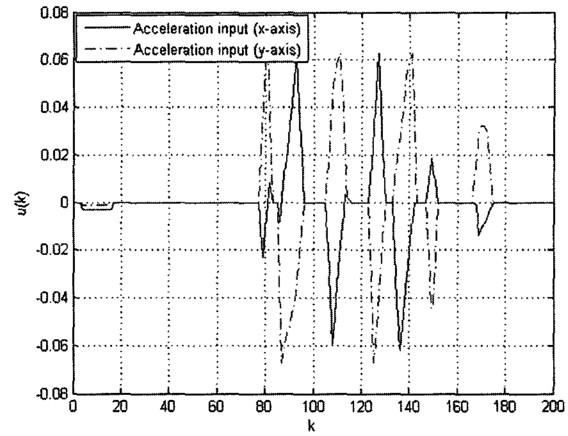


Fig. 1. The acceleration input

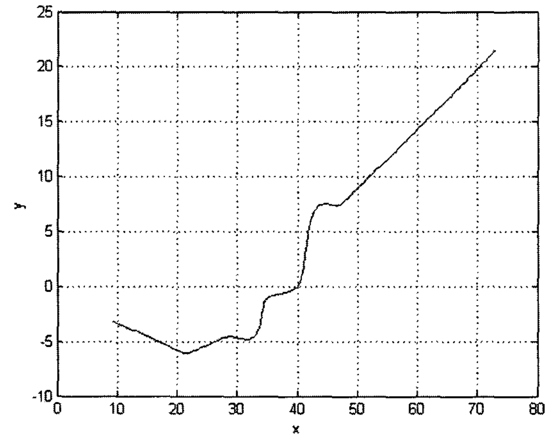
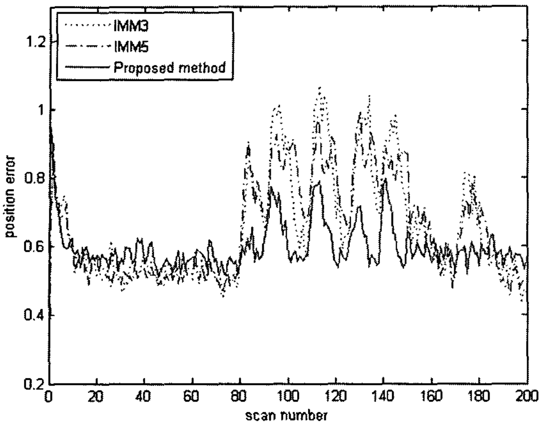


Fig. 2. The target motion

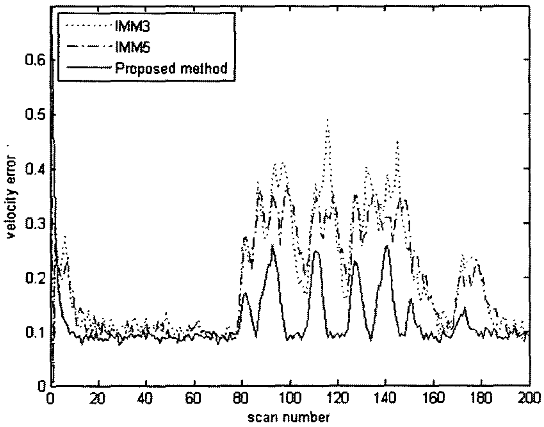
Table 3. The fuzzy rules optimized by GD

Rules	c_1	σ_1	c_2	σ_2	γ
1	0.17627	0.58279	0.27219	0.4611	0.64872×10^{-2}
2	0.40571	0.4235	0.19881	0.56783	0.25871×10^{-2}
3	0.93547	0.51551	0.015274	0.79421	0.3874×10^{-2}
4	0.9169	0.33395	0.74679	0.05918	0.98741×10^{-2}
5	0.41027	0.43291	0.4451	0.60287	0.4217×10^{-2}
6	0.89365	0.22595	0.93181	0.05026	0.68452×10^{-2}
7	0.05789	0.57981	0.46599	0.41537	0.0258×10^{-2}

Numerical results are shown in Table 4. Table 4 indicates that the normalized position and velocity errors of the proposed method are reduced by 8.48%-38.20% and 7.99%-35.97%, compared with the IMM method, and by 7.23%-27.80% and 7.14%-28.09%, respectively, compared with the AIMM method in the average sense.

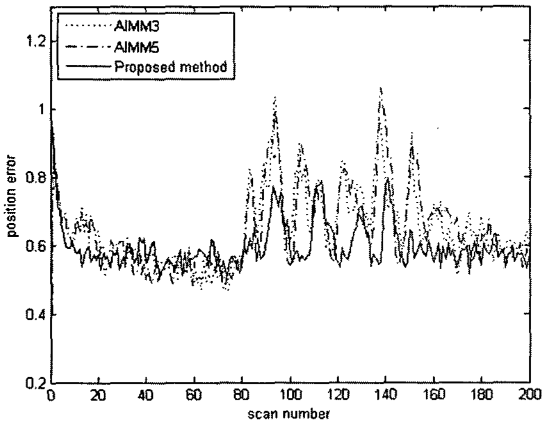


(a) Standard position error

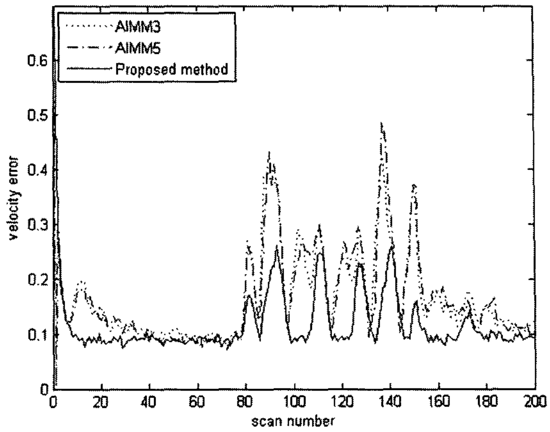


(b) Standard velocity error

Fig. 3. Comparisons of normalized position and velocity errors for proposed algorithm and IMM method



(a) Standard position error



(b) Standard velocity error

Fig. 4. The acceleration levels for the IMM and AIMM methods

Tabel 4. The comparison of the numerical results

	Configurations	No.of sub-filters	ζ_p	ζ_v
1	IMM3	3	0.6563	0.2005
2	IMM5	5	0.6556	0.1935
3	AIMM3	3	0.6502	0.1716
4	AIMM5	5	0.6496	0.1723
5	Propose Method	1	0.6032	0.1239

This implies that the proposed method provides smaller position errors and velocity errors at almost every scan time, especially during maneuvering time intervals, than the IMM and the AIMM methods.

4. Conclusions

In this paper, we have developed tracking algorithm as the new intelligent tracking method for a maneuver target. In the proposed method, the unknown acceleration input was determined by proposed 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. And then, modified filter is corrected by the new update equation method which is a fuzzy system using the relation between the filter residual and its variation. In computer simulation, we have shown the proposed filter can effectively treat a target maneuver with only one filter by comparing with IMM and AIMM.

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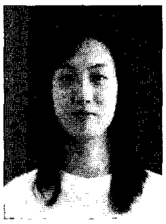

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