지능형 추적 알고리즘

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Intelligent Tracking Algorithm for Maneuvering Target

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Abstract - When the target maneuver occurs, the estimate of the standard Kalman filter is biased and its performance may be seriously degraded. To solve this problem, this paper proposes a new intelligent estimation algorithm for a maneuvering target. This algorithm is to estimate the unknown target maneuver by a fuzzy system using the relation between the filter residual and its variation. The detected acceleration input is regarded as an additive process noise. To optimize the employed fuzzy system, the genetic algorithm (GA) is utilized. And then, the modified filter is corrected by the new update equation method using the fuzzy system. The tracking performance of the proposed method is compared with those of an interacting multiple model (IMM).

Key Words : Kalman filter, maneuver target, genetic algorithm, fuzzy system

1. Introduction

Modeling of the maneuvering target system accurately is one of the most important problems when using the Kalman filter for target tracking. In the presence of unknown target maneuver, the estimates of the Kalman filter is biased, and thus an auxiliary estimation process should be implemented to compensate the error[1]. 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 over decades[2,3]. Development of an accurate system model requires maneuver detection and estimation of the magnitude of an maneuver. But it is not easy to detect the exact onset time of maneuver. 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. These processes may increase the tracking error.

To solve this problem, we propose a new intelligent fuzzy Kalman filter to reduce th additional effort required in conventional methods, improve the tracking performance, and establish the systematic tracker design procedure for a maneuvering target. When the target maneuver occurs, the unknown target acceleration input is determined by a fuzzy system using the relation between the filter residual and its variance. The determined acceleration input is regarded as an additive process noise. And then, the modified filter is corrected by the fuzzy correction gain using the new update equation method in order to correct the modeling error effectively. 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.

2. Target model

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

$$x_k = Ax_{k-1} + B(u_{k-1} + w_{k-1}) \tag{1}$$

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

where, x_k is state vector, A B are system matric, the process noise w_{k-1} is zero mean white Gaussian noise with known covariance Q_{k-1}. The measurement equation is

$$z_k = H_k x_k + v_k \tag{2}$$

where, $H=[1\ 0]$is the measurement matrix, and v_k is the measurement noise, zero mean white known covariance R_k

3. The new intelligent estimation algorithm

3.1 The unknown maneuver detection method

In this section, we propose the GA-based fuzzy Kalman filter algorithm. When the target maneuver occurs in (1), the standard Kalman filter cannot track the maneuvering target because the original process noise variance cannot cover the acceleration u_{k-1}. To treat u_{k-1} simply, we consider as an additive process noise. Hence, (1) can be rewritten as

$$x_k = Ax_{k-1} + B\overline{w}_{k-1} \tag{3}$$

where, $\overline{u}_{k-1}$ is the overall process noise with time-varying variance $\overline{q}_{k-1}$. The time-varying overall process noise variance for the fuzzy Kalman filter is inferred by a double-input single-output fuzzy system, for which the j the fuzzy IF-THEN rule is represented by

$$Rule\, j: IF\, x_1\, is\, A_{1j}\text{ and } x_2\, is\, A_{2j},\; THEN\, y\, is\, q_j \tag{4}$$

where, two premise variables are the filter residual and its variation respectively, and a consequence variable y is the process noise variance q_i. 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:

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

$\overline{q}_k$ is approximated in the following form:

$$\overline{q}_k = \frac{\sum_{j=1}^{M} q_j\left(\prod_{i=1}^{2}\mu_{ij}(x_{ij})\right)}{\sum_{j=1}^{M}\left(\prod_{i=1}^{2}\mu_{ij}(x_{ik})\right)} \tag{6}$$

To facilitate the fuzzy system to approximate $\overline{q}_k$ 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. We use the fitness function of the form.

$$f = \lambda\frac{1}{error+1} + (1-\lambda)\frac{1}{rule+1} \tag{7}$$

where, λ is a positive scalar which adjusts the weight between the objective function and the number of rules.

3.2 The 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 contain additive process noise. 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:

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

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

$$P_{k|k-1} = AP_{k-1|k-1}F^T + G\overline{q}_k G^T \tag{9}$$

The state measurement prediction of system can be rewritten as:

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

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.

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

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, $A_{ij}(i\in 1,2 \text{ and } j\in 1,2,\ldots,M)$ 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

$$E_j \cong [\overline{\gamma}_j - \tilde{z}_k]$$

$$e^p = \frac{1}{2M}\left[\sum_{j=1}^{M}E_j^2\right] \tag{14}$$

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

$$\gamma_{Fg_k} = [\,\overline{\gamma}_k\;\; \overline{\gamma}_k\,] \tag{15}$$

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:

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

4. Simulation results

The target is assumed as an incoming anti-ship missile on the $x-y$ plane [5]. The initial position of the target is at $[72.9km, 21.5km]$, and it moves with a constant velocity of $0.3km/s$ along a $-150°$ line to the x-axis. For, both axes, the standard deviation of the zero mean white Gaussian measurement noise is $0.5km$ and that of a random acceleration noise is $0.001km/s^2$.

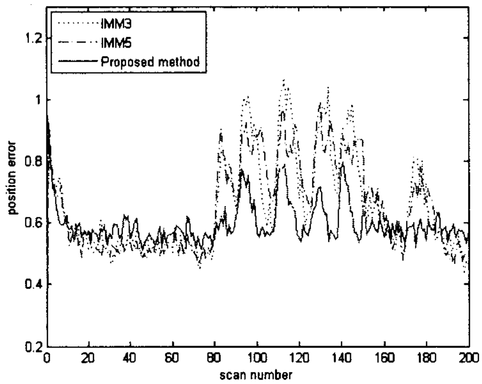
The simulation results with 100 Monte-Carlo simulations are shown Fig.1. Figure 1 shows that the simulation results of the proposed method is compared with those of the IMM method. Numerical results are shown in Table 1. Table 1 indicates that the normalized position and velocity errors of the proposed method are reduced by 8.18%-38.70% and 8.08%-36.49%, compared with the IMM method in the average sense. This implies that the proposed method provides smaller position errors and velocity errors at almost scan time, especially during maneuvering time intervals than the IMM method. This is because, although the properties of the maneuver are unknown, the time-varying variance of the overall process noise can be well approximated via the fuzzy system and once more modified filter is corrected fuzzy system, whereas the IMM methods cannot effectively deal with the complex properties of the maneuvering target.

Tabel 1. The numerical results

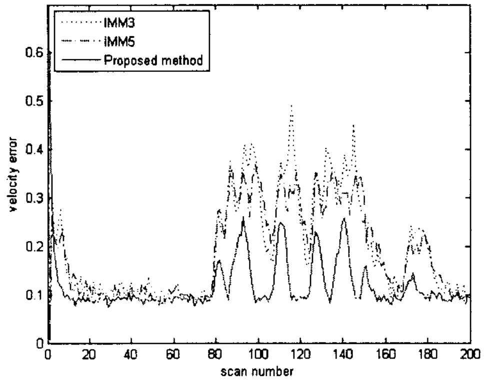
	Configurations	No. of sub-filters	ζ_p	ζ_v
1	IMM3	3	0.6563	0.2005
2	IMM5	5	0.6556	0.1935
5	Propose Method	1	0.6026	0.1229

4. Conclusions

The proposed algorithm is to estimate the unknown target maneuver by a fuzzy system using the filter residual. And, the modified filter is then corrected by the new update equation method using the fuzzy system. Finally, we have shown the proposed filter can effectively treat a target maneuver with only one filter by comparing with the IMM through computer simulations for an incoming ballistic missile.



(a) Normalized position error.



(b) Normalized velocity error.

Fig.1 The simulation results

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