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퍼지모델 기반 칼만 필터를 이용한 레이다 표적 추적

Radar Tracking Using a Fuzzy-Model-Based Kalman Filter

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ABSTRACT

In radar tracking, since the sensor measures range, azimuth and elevation angle of a target, the measurement equation is nonlinear and the extended Kalman filter (EKF) is applied to nonlinear estimation. The conventional EKF has been widely used as a nonlinear filter for radar tracking, but the considerably large measurement error due to the linearization of nonlinear function in highly nonlinear situations may deteriorate the performance of the EKF. To solve this problem, a fuzzy-model-based Kalman filter (FMBKF) is proposed for radar tracking. The FMBKF uses a local model approximation based on a TS fuzzy model instead of a Jacobian matrix to linearize nonlinear measurement equation. The hybrid GA and RLS method is used to identify the premise and the consequent parameters and the rule numbers of this TS fuzzy model. In two-dimensional radar tracking problem, the proposed method is compared with the conventional EKF.

Key words : Radar tracking, Extended Kalman filter, Fuzzy-model-based Kalman filter, TS fuzzy model, Hybrid GA and RLS method

I. Introduction

For the past three decades, the tracking problem of a moving target with radar measurements has been a fruitful application area for the state estimation. In general, the objective of target tracking is to estimate accurately the target trajectory dependent on the noisy measurements from the sensor. In radar tracking problems, since the sensor measures the range, azimuth and elevation angle of a target, the measurement equation is nonlinear and the extended Kalman filter (EKF) is applied to nonlinear estimation. The EKF has been widely used as a nonlinear filter for radar tracking. However, the usual tracking filters relying on the linear approximation lead to poor convergence and erratic behavior in highly nonlinear situations.

To resolve this problem, a fuzzy-model-based Kalman filter (FMBKF) is proposed for radar tracking. The FMBKF uses a local model approximation based on a TS fuzzy model instead of a Jacobian matrix to linearize nonlinear measurement equation. In the proposed method, to identify the premise and the consequent parameters and the rule numbers of this TS fuzzy model, the hybrid GA and RLS method is used as an optimization learning method to search more globally optimal solution.

The proposed FMBKF is applied and simulated in two-dimensional radar tracking problem. Computer simulation is divided by two parts-one is simulation for offline optimization of TS fuzzy model and the other is the Monte Carlo simulation for radar tracking using the optimized TS fuzzy model. The FMBKF is compared with the conventional EKF.

II. Problem Statement

In a two-dimensional Cartesian co-ordinate system, the target motion model is described by the following linear discrete-time difference equation with additive noise that models unpredictable disturbances:

$$\mathbf{x}_{k+1} = F_k \mathbf{x}_k + G_k \mathbf{v}_k$$

where the state $\mathbf{x}_k = [x_k \ y_k \ \dot{x}_k \ \dot{y}_k]^T$ consists of the position and the velocity of a moving target, and process noise $\mathbf{v}_k$ is assumed to be white and zero-mean with covariance

$$E[\mathbf{v}_k \mathbf{v}_k^T] = Q_k .$$

The target is tracked by radar on the origin and the sensor measures range r and azimuth θ of the target. The measurement equation is described by the following nonlinear discrete equation

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{w}_k = \begin{bmatrix} (x_k^2 + y_k^2)^{1/2} \\ \tan^{-1}(y_k / x_k) \end{bmatrix} + \begin{bmatrix} w_r \\ w_\theta \end{bmatrix} \qquad (1)$$

where the measurement noise w_r and w_θ are assumed to be white, Gaussian, mutually uncorrelated, and zero-mean with covariance

$$R_k = \mathrm{diag}\{\sigma_r^2,\ \sigma_\theta^2\}.$$

The basic task of this paper is to optimize the TS fuzzy model to be used in the linearization of nonlinear function and to estimate as accurately as possible the target trajectory from the radar measurements using the optimized TS fuzzy model.

III. FMBKF for Radar Tracking

3.1. EKF

In the EKF, the nonlinear measurement function of (1) is approximated as follows:

$$\mathbf{h}(\mathbf{x}_k) \approx \mathbf{h}(\hat{\mathbf{x}}_{k|k-1}) + H_k(\mathbf{x}_k - \hat{\mathbf{x}}_{k|k-1}) \qquad (2)$$

where H_k is the Jacobian of $\mathbf{h}(\cdot)$ evaluated at the predicted state estimate $\hat{\mathbf{x}}_{k|k-1}$:

$$H_k = \left.\frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}}\right|_{\mathbf{x}=\hat{\mathbf{x}}_{k|k-1}} = \begin{bmatrix} \cos\bar{\theta}_k & \sin\bar{\theta}_k & 0 & 0 \\ -\dfrac{\sin\bar{\theta}_k}{\bar{r}_k} & \dfrac{\cos\bar{\theta}_k}{\bar{r}_k} & 0 & 0 \end{bmatrix}$$

where the prediction of range $\bar{r}_k$ and azimuth $\bar{\theta}_k$ are defined by

$$\bar{r}_k = (\hat{x}_{k|k-1}^2 + \hat{y}_{k|k-1}^2)^{1/2}$$

$$\bar{\theta}_k = \tan^{-1}(\hat{y}_{k|k-1} / \hat{x}_{k|k-1})$$

The EKF algorithm using Jacobian linearization is summarized as follows:

State prediction and its covariance

$$\hat{\mathbf{x}}_{k|k-1} = F_{k-1}\hat{\mathbf{x}}_{k-1|k-1} \qquad (3)$$

$$P_{k|k-1} = F_{k-1}P_{k-1|k-1}F_{k-1}^T + G_{k-1}Q_{k-1}G_{k-1}^T \qquad (4)$$

Kalman Gain

$$K_k = P_{k|k-1}H_k^T[H_k P_{k|k-1} H_k^T + R_k]^{-1} \qquad (5)$$

Updated state estimate and its covariance

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + K_k[\mathbf{z}_k - \mathbf{h}(\hat{\mathbf{x}}_{k|k-1})] \qquad (6)$$

$$P_{k|k} = [I - K_k H_k]P_{k|k-1} \qquad (7)$$

3.2. FMBKF

The FMBKF uses a local model approximation based on a TS fuzzy model instead of a Jacobian matrix to linearize nonlinear measurement equation. The j th ($j = 1\Lambda\ n$) TS fuzzy rule for each nonlinear measurement equation is as follows:

$$\text{IF } \chi_1 \text{ is } A_1^j \text{ and } \chi_2 \text{ is } A_2^j,$$

$$\text{THEN } y = p_1^j \chi_1 + p_2^j \chi_2$$

where input vector $\bar{\mathbf{x}}_k$ is the measured position in each axis as follows:

$$\bar{\mathbf{x}}_k = [\chi_1 \ \chi_2]^T = [x_k^m \ y_k^m]^T = [r_k^m \cos\theta_k^m \ \ r_k^m \sin\theta_k^m]^T$$

y means the output of each nonlinear measurement equation and is represented in the form of linear combination of $\bar{\mathbf{x}}_k$. A_i^j ($i = 1,2$) is the Gaussian membership function with membership grade $\mu_i^j(x_i)$ described as

$$\mu_i^j(x_i) = \exp\left[-\frac{1}{2}\left(\frac{x_i - c_i^j}{\sigma_i^j}\right)^2\right] \qquad (9)$$

where c_i^j and σ_i^j are the center and the standard deviation of the Gaussian membership function respectively.

By product inference and weighted average defuzzification, the output of this fuzzy system y for the input $\bar{\mathbf{x}}_k$ is obtained as

$$y = \frac{\sum_{j=1}^{n}[\mu_1^j(x_1)\mu_2^j(x_2)]\cdot[p_1^j x_1 + p_2^j x_2]}{\sum_{j=1}^{n}[\mu_1^j(x_1)\mu_2^j(x_2)]}$$

Let β^j be

$$\beta^j = \frac{[\mu_1^j(x_1)\mu_2^j(x_2)]}{\sum_{j=1}^{n}[\mu_1^j(x_1)\mu_2^j(x_2)]}$$

then

$$y = \sum_{j=1}^{n}\beta^j[p_1^j x_1 + p_2^j x_2] = \sum_{j=1}^{n}[\beta^j p_1^j x_1 + \beta^j p_2^j x_2]$$

Thus the nonlinear measurement function $\mathbf{h}(\mathbf{x}_k)$ is approximated in the FMBKF as follows:

$$\mathbf{h}(\mathbf{x}_k) \approx [h_1^j(\bar{\mathbf{x}}_k)\ h_2^j(\bar{\mathbf{x}}_k)]^T = \sum_{j=1}^{n}\mathrm{H}_k\bar{\mathbf{x}}_k \quad (10)$$

where $h_l^j(\bar{\mathbf{x}}_k)$ means the l th $(l=1,2)$ measurement equation of $\mathbf{h}(\mathbf{x}_k)$ for j th fuzzy rule and H_k is the measurement matrix denoted as follows.

$$\mathrm{H}_k = \begin{bmatrix} \beta_1^j p_{11}^j & \beta_1^j p_{12}^j & 0 & 0 \\ \beta_2^j p_{21}^j & \beta_2^j p_{22}^j & 0 & 0 \end{bmatrix} \quad (11)$$

where β_l^j means the value of β^j for the l th measurement equation of $\mathbf{h}(\mathbf{x}_k)$.

Finally, we can rewrite the measurement equation in the following form

$$\mathbf{z}_k^F = \sum_{j=1}^{n}\mathrm{H}_k\mathbf{x}_k + \mathbf{w}_k = \sum_{j=1}^{n}\begin{bmatrix} \beta_1^j p_{11}^j & \beta_1^j p_{12}^j & 0 & 0 \\ \beta_2^j p_{21}^j & \beta_2^j p_{22}^j & 0 & 0 \end{bmatrix}\mathbf{x}_k + \mathbf{w}_k \quad . (12)$$

Now, we can apply the standard Kalman filter algorithm and the FMBKF algorithm is as follows:

State prediction and its covariance

$$\hat{\mathbf{x}}_{k|k-1} = F_{k-1}\hat{\mathbf{x}}_{k-1|k-1} \quad (13)$$

$$P_{k|k-1} = F_{k-1}P_{k-1|k-1}F_{k-1}^T + G_{k-1}Q_{k-1}G_{k-1}^T \quad (14)$$

Kalman Gain

$$K_k^F = \sum_{j=1}^{n}(P_{k|k-1}H_k^{j^T})[\sum_{j=1}^{n}(H_k^j P_{k|k-1}H_k^{j^T}) + R_k]^{-1} \quad (15)$$

Updated state estimate and its covariance

$$\hat{\mathbf{x}}_{k|k}^F = \hat{\mathbf{x}}_{k|k-1} + K_k[\mathbf{z}_k - \sum_{j=1}^{n}(H_k^j\hat{\mathbf{x}}_{k|k-1})] \quad (16)$$

$$P_{k|k}^F = [I - \sum_{j=1}^{n}(K_k H_k^j)]P_{k|k-1} \quad (17)$$

3.3. Identification of TS fuzzy model

In this paper, the hybrid GA and RLS method is used to identify the TS fuzzy model. The GA is used to identify the premise parameters and the rule numbers of TS fuzzy model, and the RLS method is used to identify the consequent parameters.

The procedure of training using the GA and RLS method is described in fig. 1.

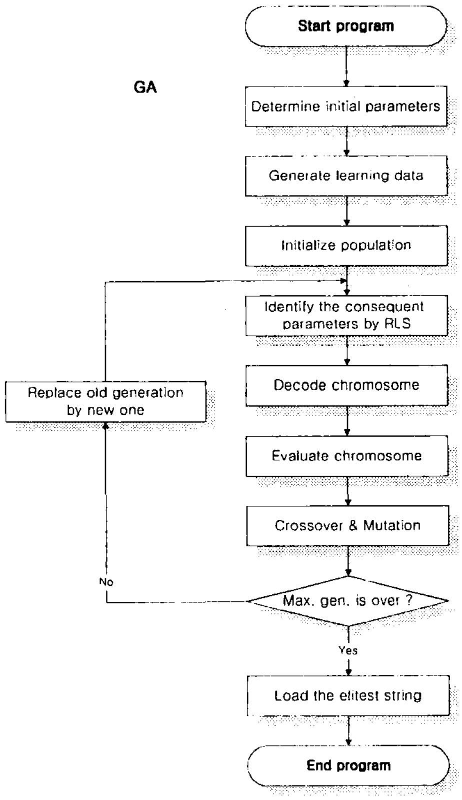


Fig. 1 The procedure for learning using the hybrid GA and RLS method

The fitness of the individual is determined in inverse proportion to the square error (SE) and the number of rules.

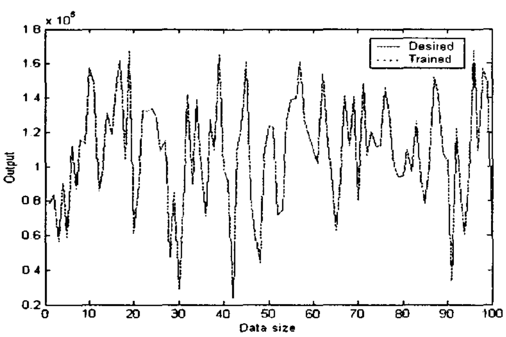
$$\text{fitness} = \lambda \frac{1}{\text{SE}+1} + (1-\lambda)\frac{1}{\text{rule number}+1} \quad (18)$$

where λ means the relative value between MSE and rule number.

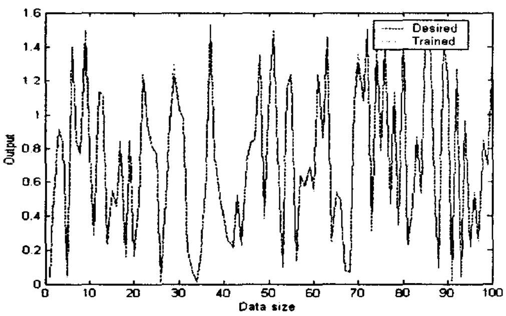
IV. Simulations

Computer simulation was divided by two parts−one was simulation for offline optimization of TS fuzzy model and the other was the Monte Carlo simulation for radar tracking using the optimized TS fuzzy model.

Figure 2 shows the training results using the hybrid GA and RLS method.



(a) 1^{st} function ($(x_k^2 + y_k^2)^{1/2}$)



(b) 2^{nd} function ($\tan^{-1}(y_k / x_k)$)

Fig. 2 Training results

Incoming target was considered and the initial state of the target was

$$[150km \quad 120km \quad -125m \quad -125m]^T,$$

the standard deviation of process noise was set at $0.5m/s^2$ for each axis, and those of measurement noises were assumed to be $50m$ and 2° for range and azimuth, respectively. The result for a Monte Carlo simulation of 200 runs is shown in Fig. 3.

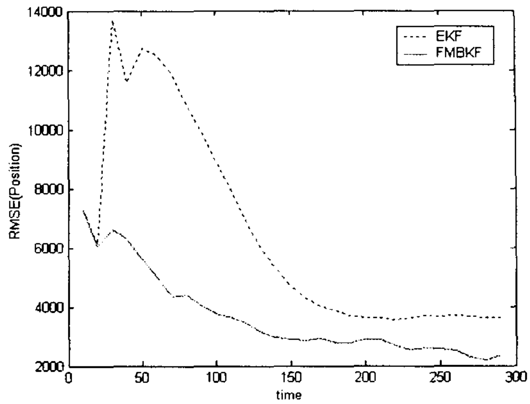


Fig. 3 Simulation result

V. Conclusions

In this paper, we proposed the fuzzy−model−based Kalman filter (FMBKF) using a local model approximation based on a TS fuzzy model. The hybrid GA and RLS method was used to identify the premise and the consequent parameters and the rule numbers of the TS fuzzy model. The proposed FMBKF was applied and simulated in two−dimensional radar tracking problem. The simulation results have shown that the FMBKF had much superior performance to the conventional EKF.

VI. 참고문헌

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