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Maneuvering target tracking using fuzzy logic-based recursive least squares filter

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Abstract

In this paper, a fuzzy logic-based recursive least squares filter (FLRLSF) is presented for maneuvering target tracking (MTT) in situations of observations with unknown random characteristics. In the proposed filter, fuzzy logic is applied in the standard recursive least squares filter (RLSF) by the design of a set of fuzzy if-then rules. Given the observation residual and the heading change in the current prediction, these rules are used to determine the magnitude of the fading factor of RLSF. The proposed filter has an advantage in which the restrictive assumptions of statistical models for process noise, measurement noise, and motion models are relaxed. Moreover, it does not need a maneuver detector when tracking a maneuvering target. The performance of FLRLSF is evaluated by using a simulation and real test experiment, and it is found to be better than those of the traditional RLSF, the fuzzy adaptive α-β filter (FAα-βF), and the hybrid Kalman filter in tracking accuracy.

Keywords: Maneuvering target tracking; Adaptive filter; Recursive least squares filter; Fading factor; Fuzzy logic; Heading change

1 Introduction

Maneuvering target tracking (MTT) is always a critical problem in target tracking area [1-5]. In the literature on MTT in sensor network, its survey primarily consists of target dynamic models, observation models and techniques, decision-based methods, multiple-model methods, and nonlinear filtering methods. The adaptive filters are popular to apply in MTT as a nonlinear-type filter; they are mainly classified as follows [2]: structured adaptive filters, such as the interacting multiple model (IMM) and the variable structured model; parametric adaptive filters, such as the Singer model, the current statistical model, and the adaptive acceleration model. Structured adaptive filters, usually with more computation, require sufficient prior knowledge such as all possible motion models of a moving target. So, they are less suitable for real situations with limited prior knowledge. Parametric adaptive filters, generally with less computation, describe maneuver characteristics as unknown random parameters with certain probability distribution functions (pdf) and estimate maneuver models jointly by both the parameters and the target

states [2]. Recently, particle filters are broadly adopted in various applications, such as location estimation [6-8]. However, their tracking performances are combined in proportion to the number of the corresponding particles in target tracking. Moreover, the computation of these filters is generally complicated. Hence, they are unsuitable to apply in real-time tracking [9-11]. In real sensor networks, observations or state estimates are generally transmitted without their covariances. They are processed in sensor nodes or fusion centers. To relax transmission burdens and save communication bandwidths, the filters designed need to possess good performances in both computational and time complexity. For the above reasons, this paper is only concerned with parametric adaptive filters.

Maneuver modeling which is a usual prerequisite for MTT has a direct influence on tracking results [5]. Several techniques have been introduced to overcome different maneuver modeling. MTT methods based on statistical models often need to establish motion models exactly and obtain the target position timely. Unfortunately, these requirements are difficult to satisfy because of unknown maneuver characteristics in real situations. To solve the problem, one of the most popular techniques has been applied in MTT. Fuzzy logic with

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intelligent adaptation capabilities has been widely used to relax or avoid the restrictive assumptions of motion models [12-16]. Due to the limitation of the standard IMM algorithm in real applications, the adaptive fuzzy IMM filter (AFIMMF) proposed in [12] defines several basis sub-models and time-varying mode transition probabilities to reduce its computational complexity. Nevertheless, it suffers from a deficiency originated in expensive computation of the time-varying mode transition probabilities. Moreover, its performance depends on the assumptions on the basis sub-models. Two different modified Kalman filters proposed in [13] and [14] tend to extend the standard Kalman filter for MTT. Nonetheless, their computation is still expensive, and the proposed hybrid Kalman filter (HKF) in [14] is mainly applied to track an accelerating target. To track a target making sharp turns or accelerating at nonuniform rates in stressful environments, the fuzzy gain α-β filter (FGα-βF) is proposed in [15]. It can avoid any assumptions on statistical models by utilizing fuzzy rules to determine the magnitudes of α and β. However, its tracking result in the case where sharp turns appear is not improved markedly. For perfect tracking accuracy, the fuzzy adaptive α-β filter (FAα-βF) proposed in [16] can detect maneuvers. However, its tracking result is still undesirable.

In practice, the standard recursive least squares filter (RLSF) [17,18] is quite well received in linear models with the unknown random characteristics of observations. In this case, it has less computational complexity than the standard Kalman filter. Unfortunately, its performance degrades seriously during maneuvering. For perfect output results in nonlinear models, the traditional fuzzy adaptive filters make the relationship between the input and output variables maps into a set of fuzzy rules, and these rules determine the control parameters of the filters. So, their performances depend on whether the rules can describe maneuver characteristics exactly and completely. Due to the unknown motion models during real tracking procedures, a complex nonlinear relationship exists between observations and state estimates. For this reason, the fuzzy rules are usually difficult to establish by directly utilizing the relationship between the observations and the state estimates. Therefore, the traditional fuzzy adaptive filters are restricted in the applications of MTT.

Applying fading factors and fuzzy logic into traditional filters are popular because of some practical concerns including easy implementation and effectiveness. In this respect, it provides a direction to design a filter for MTT [19]. Considering these facts, a novel fuzzy logic-based recursive least squares filter (FLRLSF) is proposed to deal with the problem mentioned above. First, the proposed filter utilizes observation residuals and heading changes to describe maneuver characteristics of a maneuvering target

and employs the fading factor of RLSF to express the magnitude of the target maneuver. A set of fuzzy rules is designed according to the relationship of the fading factor with observation residuals and heading changes over time. Next, given the observation residual and the heading change in the current prediction, these rules are applied to determine the magnitude of the fading factor. Then, the fuzzy system designed based on the rules is utilized to adjust the fading factor in response to the changes in speed and direction without maneuver detectors. Finally, FLRLSF is applied to estimate the target state. Its performance is evaluated by using a simulation and real test experiment, compared with the existing filters mentioned above.

2 Analysis of maneuvering target motions

Target motion models form two categories, the linear and maneuver (nonlinear) models. In linear models, the motion and observation model of a moving target are defined as follows:

$$x_{k+1} = \Phi_k x_k + v_k \tag{1}$$

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

where x_k denotes an n-dimensional state vector about the target at time k and z_k denotes an m-dimensional observation vector. Φ_k is an $n \times n$ state transition matrix, and H_k is an $m \times n$ observation transition matrix. The process noise v_k is assumed to be Gaussian white noise with zero mean and covariance Q_k, while the observation noise w_k is assumed to be the zero-mean Gaussian noise with the covariance R_k.

$$E[v_k v_t] = Q_k \delta_{kt} \tag{3}$$

$$E[w_k w_t] = R_k \delta_{kt} \tag{4}$$

where is δ_{kt} the Kronecker delta function.

Though targets often move at constant velocity, they are easy to maneuver suddenly. In this respect, maneuver modeling is a key problem of MTT. To solve this problem, many methods have been proposed on the restrictive assumptions of the motion models [17,20]. Considering the aforementioned facts, these assumptions are often inconsistent with real environments. Then, two strategies of motion modeling exist with unknown maneuver information: describe the target trajectory as several typical motion models with known parameters or their combination [3] or incorporate control variables in the target motion equation as the random variables with the certain pdf [20]. Unfortunately, it is difficult to obtain the prior information in real situations, and various uncertainties generally exist in maneuver motions during real tracking procedures [16]. So, the methods based on the statistic framework are complicated and difficult due

to establishing the accurate motion models or obtaining the exact pdf by using the probability and statistics theory. Nowadays, fuzzy systems with the universal approximation capabilities have been widely applied in nonlinear complicated system [21,22]. Incorporation of fuzzy logic in fuzzy systems is easy and flexible to describe various uncertainties or random variables by the use of linguistic terms. From this point of view, it is a good idea that fuzzy systems are designed to adjust the filter parameter for MTT.

In addition, observations from a target contain much information of kinematics characteristics, whether the target maneuvers or moves at constant velocity. Theoretically, applying characteristic information into filter estimation can help the maneuvering modeling and improve the performances of tracking results. In various characteristics, observation residuals and heading changes are two important characteristics of the motion model. They can perfectly reflect the relationship between observations and maneuvers. On the one hand, if observation residual or heading change is large, the target is strongly maneuvering with high probability. On the other hand, if the observation residual or heading change is small, the target is weakly maneuvering with high probability. In addition, incorporation of them in tracking methods may lead to an immediate detection and a less delay about maneuvers [2,14,16]. Considering this fact, observation residuals and heading changes are usually combined to detect maneuvers. They can be calculated with the following relations:

$$\Delta z_k = \left[(z_k - H_k \Phi_k \hat{x}_{k-1})^{\mathrm{T}} (z_k - H_k \Phi_k \hat{x}_{k-1}) \right]^{1/2} \quad (5)$$

$$\Delta \theta_k = |\varphi_k - \phi_{k-1}| \quad (6)$$

where Δz_k and $\Delta \theta_k$ denote observation residual and heading change; ϕ_k is the angle between the observation vector z_k and the state estimate vector, while ϕ_{k-1} is the angle between the state estimate vector and the state estimate vector ; and the superscript T denotes transpose. Here, φ_k and ϕ_{k-1} are obtained from the following forms:

$$\varphi_k = \arctan \left[(y_k - \hat{y}_{k-1}) / (x_k - \hat{x}_{k-1}) \right] \quad (7)$$

$$\phi_{k-1} = \arctan \left[(\hat{y}_{k-1} - \hat{y}_{k-2}) / (\hat{x}_{k-1} - \hat{x}_{k-2}) \right] \quad (8)$$

where x_k, $\hat{x}_{k-1}$, and $\hat{x}_{k-2}$ are the components of z_k, $\hat{x}_{k-1}$, and $\hat{x}_{k-2}$ in the x-axis direction respectively, while y_k, $\hat{y}_{k-1}$, and $\hat{y}_{k-2}$ are their corresponding components in the y-axis direction. To simplify both computation and discussion, Δz_k and $\Delta \theta_k$ are necessary in normalization processing with the following forms: $\Delta z_k' = \Delta z_k / \Delta z_{\max}$ and $\Delta \theta_k' = \Delta \theta_k / \Delta \theta_{\max}$ instead of Δz_k and $\Delta \theta_k$. Here, $\Delta z_{\max}$ and $\Delta \theta_{\max}$ are their corresponding maximum

values, and they are usually related with the target's type and the sensor's performance.

3 Traditional RLSF method

RLSF is an effective estimate method in a linear motion model, and it is widely used to estimate the target state in target tracking [17,18]. Using Equation 2, one can obtain at time k

$$z^k = H^k x_k + w^k \quad (9)$$

where $z^k = (z_1, z_2, ..., z_k)^{\mathrm{T}}$, $H^k = (H_1, H_2, ..., H_k)^{\mathrm{T}}$, and $w^k = (w_1, w_2, ..., w_k)^{\mathrm{T}}$.

Give the quadratic error function C_k as follows:

$$C_k = \left(z^k - H^k x_k \right)^{\mathrm{T}} F_k \left(z^k - H^k x_k \right) \quad (10)$$

where F_k is a diagonal matrix, whose main diagonal elements are λ_k^{k-1}, ..., λ_k, 1. Here, λ_k is called the fading factor lied in (0,1]. The least squares estimate vector equals the corresponding value x_k when C_k obtains its minimum value. To obtain $\hat{x}_k$, the function (10) is differentiated for x_k to yield

$$\nabla_{x_k} C_k = \frac{\partial}{\partial x_k} \left(z^k - H^k x_k \right)^{\mathrm{T}} F_k \left(z^k - H^k x_k \right) \quad (11)$$

so that $\hat{x}_k$ is derived by solving Equation 11 for x_k

$$\hat{x}_k = P_k \left(H^k \right)^{\mathrm{T}} F_k z^k \quad (12)$$

where P_k is the estimate error covariance at time k, calculated in the following form:

$$P_k = \left[\left(H^k \right)^{\mathrm{T}} F_k H^k \right]^{-1} \quad (13)$$

As a result, Equations 12 and 13 can be rewritten in the recursive formularies, respectively,

$$\hat{x}_k = \Phi_k \hat{x}_{k-1} + P_k H_k^{\mathrm{T}} (z_k - H_k \Phi_k \hat{x}_{k-1}) \quad (14)$$

$$P_k = \lambda_k^{-1} \Phi_k P_{k-1} \Phi_k^{\mathrm{T}} - \lambda_k^{-2} \Phi_k P_{k-1} \Phi_k^{\mathrm{T}} H_k^{\mathrm{T}}$$
$$\times \left(I + \lambda_k^{-1} H_k \Phi_k P_{k-1} \Phi_k^{\mathrm{T}} H_k^{\mathrm{T}} \right) - 1 H_k \Phi_k P_{k-1} \Phi_k^{\mathrm{T}} \quad (15)$$

for $k \geq 3$. Equations 14 and 15 are called RLSF for x_k [18]. The initial state is determined with the observations z_1 and z_2 at time $k = 1, 2$ as follows:

$$\hat{x}_2 = P_2 \left(H^2 \right)^{\mathrm{T}} z^2 \quad (16)$$

$$P_2 = \left[\left(H^2 \right)^{\mathrm{T}} H^2 \right]^{-1} \quad (17)$$

From Equations 14 and 15, $\hat{x}_k$ is the sum of the state prediction and the deviation between the observation and the predicted position at time k on the one hand, and the magnitude of $\hat{x}_k$ depends on how large the

deviation is modified by P_k on the other hand. Meanwhile, P_k can vary with λ_k. From this point of view, $\hat{x}_k$ can be indirectly modified by adjusting λ_k. While the modification of $\hat{x}_k$ becomes weaker with the increase of λ_k, it becomes greater with the decrease of λ_k. In this respect, if one can obtain the right λ_k according to maneuver information, it implies that $\hat{x}_k$ can be exactly expressed as the modified value by adjusting λ_k at each discrete time. Therefore, RLSF can be applied to estimate the target state by employing λ_k to describe maneuver characteristics.

4 FLRLSF method for MTT

As the results in Sections 2 and 3 show, $\Delta z_k'$ and $\Delta\theta_k'$ can be combined to detect maneuvers, and λ_k can be employed to describe maneuver characteristics. Considering this fact, FLRLSF can be applied in MTT. It is illustrated in Figure 1. In the figure, block 1 calculates $\Delta z_k'$ and $\Delta\theta_k'$ based on z_k and $\hat{x}_{k-1}$. Blocks 2 to 5 compose a fuzzy system to obtain the optimum $\tilde{\lambda}_k$, elaborated in Section 4.1. Block 6 is RLSF, which can obtain the optimal state estimate $\hat{x}_k$ by the optimum $\tilde{\lambda}_k$ calculated by the fuzzy system. For clarity and perception, the fading factor is defined as a fuzzy variable, *viz.* replacing λ_k with $\tilde{\lambda}_k$. Here, the main functions of the fuzzy system give as follows: first, map the relationship of $\tilde{\lambda}_k$ with $\Delta z_k'$ and $\Delta\theta_k'$ into a set of fuzzy rules; then, according to these rules, take $\Delta z_k'$ and $\Delta\theta_k'$ as the input variables of the fuzzy system and express its output variable as the value of $\tilde{\lambda}_k$; finally, estimate the target state by adjusting $\tilde{\lambda}_k$ to modify $\hat{x}_k$.

4.1 Design of the fuzzy system

As shown in Figure 1, the design procedure of the fuzzy system, which consists of four blocks, includes the following: first, utilize a singleton fuzzifier as block 2; next, design the fuzzy rules of block 3 according to the relationship between the input and output variable of block 4; then, determine the reference engine of block 4, which maps the spaces of all variables into the fuzzy spaces and gives their membership functions; finally, select a defuzzifier of block 5. Each step is elaborated in detail as follows.

The values of two input variables are mapped into four fuzzy sets, respectively, which are expressed as $\tilde{A}_i$ and $\tilde{B}_j$, $i, j = 1, 2, 3, 4$, defined in the universe of $\Delta z_k'$ and $\Delta\theta_k'$. These fuzzy sets are labeled in the linguistic terms of zero (ZE), small positive (SP), medium positive (MP), and large positive (LP). To ensure the probability of each input data point of $\Delta z_k'$ or $\Delta\theta_k'$ falling into each fuzzy set be roughly equal, each fuzzy set is assigned to an interval of equal width and similar rules. In addition, triangular functions can simplify the computation of fuzzy reference engines and suppress the noise of input variables. So, they are used to define the membership functions of $\Delta z_k'$ or $\Delta\theta_k'$ in the corresponding universe for each fuzzy rule shown in Figure 2. The output consequence of the fuzzy system is expressed as the value of $\tilde{\lambda}_k$. It turns out that the performance of RLSF for MTT is more comfortable when the optimum $\tilde{\lambda}_k$ is found more often in the interval (0, 0.3]. Based on the fact, to obtain the optimum $\tilde{\lambda}_k$, the region of $\tilde{\lambda}_k$ is divided into six different fuzzy sets, ZE, SP, MP, VP, large positive (LP), and extremely large positive (EP), expressed as $\tilde{C}_m$, $m = 1, 2, ..., 6$. The membership function
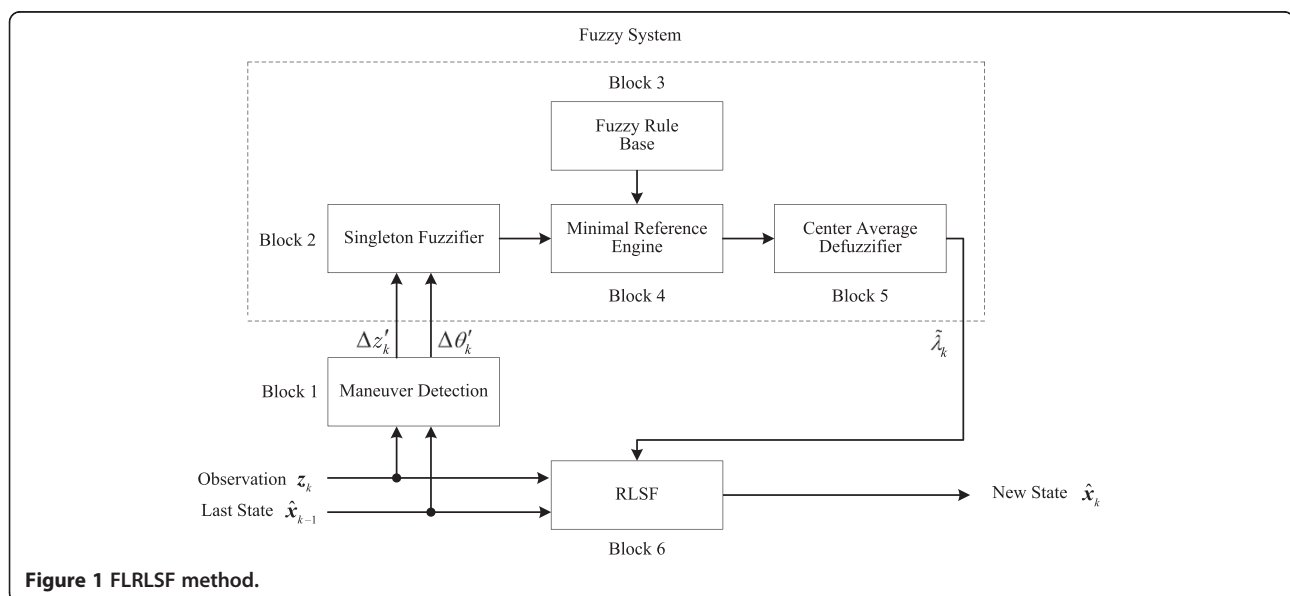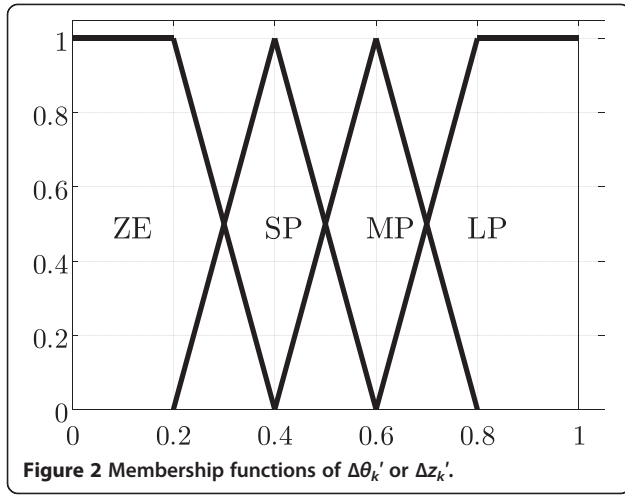

Figure 1 FLRLSF method.

Figure 2 Membership functions of $\Delta\theta_k'$ or $\Delta z_k'$.

of $\Delta z_k'$ in each fuzzy set is determined in the following formula:

$$\mu_{\tilde{A}_i^l}\left(\Delta z_k'\right) = 1 - \frac{\left|\Delta z_k' - c_i^l\right|}{b_i^l}, \Delta z_k' \in \left[c_i^l - b_i^l, c_i^l + b_i^l\right] \quad (18)$$

where b_i^l and c_i^l are the control parameters. The membership functions of $\Delta\theta_k'$ and $\tilde{\lambda}_k$ are similarly defined as $\Delta z_k'$, as shown in Figures 2 and 3, respectively.

Utilize the fuzzy rules to establish the fuzzy model of the relationship of $\tilde{\lambda}_k$ with $\Delta z_k'$ and $\Delta\theta_k'$:

$$R^l : \text{IF } \Delta z_k' \in \tilde{A}_i^l \text{ AND } \Delta\theta_k' \in \tilde{B}_j^l \text{ THEN } \tilde{\lambda}_k \in \tilde{C}_m^l \quad (19)$$

where $i, j = 1, 2, 3, 4, l = 1, 2, \ldots, M$, and $M = 16$. The requirement for adjusting $\tilde{\lambda}_k$ is given below: if $\Delta z_k'$ or $\Delta\theta_k'$ increases, then it indicates that the maneuver gets stronger and $\tilde{\lambda}_k$ needs to be set relatively small; otherwise, if $\Delta z_k'$ or $\Delta\theta_k'$ decreases, then it indicates that the maneuver

Figure 3 Membership functions of $\tilde{\lambda}_k$.
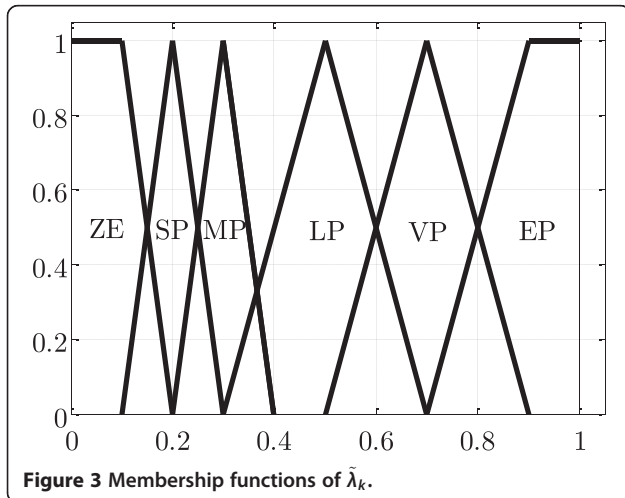
gets weaker and $\tilde{\lambda}_k$ needs to be set relatively large. The fuzzy rule base is designed as shown in Table 1.

Due to less computation and more explicitness of both the minimal reference engine and the center average defuzzier, they are usually combined to establish a fuzzy system. The minimal reference engine and the center average defuzzier are expressed in the following forms [21]:

$$\mu_{\tilde{C}_m^l}\left(\bar{\lambda}_k^l\right) = \min\left(\mu_{\tilde{A}_i^l}\left(\Delta z_k'\right), \mu_{\tilde{B}_j^l}\left(\Delta\theta_k'\right)\right) \quad (20)$$

$$\tilde{\lambda}_k = \frac{\sum_{l=1}^{M} \bar{\lambda}_m^l \mu_{\tilde{C}_m}^l\left(\bar{\lambda}_k^l\right)}{\sum_{l=1}^{M} \mu_{\tilde{C}_m}^l\left(\bar{\lambda}_k^l\right)} \quad (21)$$

As a result, the fuzzy system is given as follows:

$$f\left(\Delta z_k', \Delta\theta_k'\right) = \frac{\sum_{l=1}^{M} \bar{\lambda}_m^l \left[\min\left(\mu_{\tilde{A}_i^l}\left(\Delta z_k'\right), \mu_{\tilde{B}_j^l}\left(\Delta\theta_k'\right)\right)\right]}{\sum_{l=1}^{M}\left[\min\left(\mu_{\tilde{A}_i^l}\left(\Delta z_k'\right), \mu_{\tilde{B}_j^l}\left(\Delta\theta_k'\right)\right)\right]}$$

$$(22)$$

where $\mu_{\tilde{A}_i^l}$, $\mu_{\tilde{B}_j^l}$, and $\mu_{\tilde{C}_m}^l$ denote the membership functions of $\Delta z_k'$, $\Delta\theta_k'$, and $\tilde{\lambda}_k$, respectively; $\bar{\lambda}_k^l$ at each discrete time is equivalent to the corresponding value of $\tilde{\lambda}_k$ when the membership function of $\tilde{\lambda}_k$ is maximized at each fuzzy set defined on.

4.2 FLRLSF method

As described at the beginning of Section 4, FLRLSF is able to detect the target maneuver and estimate its state by the fuzzy system. Based on the above conclusions, the recursive form of FLRLSF is expressed as

$$\hat{x}_k = \Phi_k \hat{x}_{k-1} + P_k H_k^{\text{T}}(z_k - H_k \Phi_k \hat{x}_{k-1}) \quad (23)$$

$$P_k = \tilde{\lambda}_k^{-1} \Phi_k P_{k-1} \Phi_k^{\text{T}} - \tilde{\lambda}_k^{-2} \Phi_k P_{k-1} \Phi_k^{\text{T}} H_k^{\text{T}}$$
$$\times \left(I + \tilde{\lambda}_k^{-1} H_k \Phi_k P_{k-1} \Phi_k^{\text{T}} H_k^{\text{T}}\right) - 1 H_k \Phi_k P_{k-1} \Phi_k^{\text{T}} \quad (24)$$

Table 1 Fuzzy rules on $\Delta\theta_k'$, $\Delta z_k'$, and $\tilde{\lambda}_k$

		$\Delta\theta_k'$			
		ZE	**SP**	**MP**	**LP**
$\Delta z_k'$	ZE	EP	EP	LP	MP
	SP	EP	VP	MP	SP
	MP	LP	MP	SP	ZE
	LP	MP	SP	ZE	ZE

where

$$\tilde{\lambda}_k = \frac{\sum_{l=1}^{M} \bar{\lambda}_m^l \sup_{\Delta z_k' \in \tilde{A}_i^l, \Delta \theta_k' \in \tilde{B}_j^l} \min\left(\mu_{\tilde{A}_i^l}(\Delta z_k'), \mu_{\tilde{B}_j^l}(\Delta \theta_k')\right)}{\sum_{l=1}^{M} \sup_{\Delta z_k' \in \tilde{A}_i^l, \Delta \theta_k' \in \tilde{B}_j^l} \min\left(\mu_{\tilde{A}_i^l}(\Delta z_k'), \mu_{\tilde{B}_j^l}(\Delta \theta_k')\right)}$$

(25)

The FLRLSF flow chart in each period is illustrated in Figure 4.

4.3 Computational complexity analysis

Computational complexity for an algorithm is an important index whether the algorithm provides processing capability in real time, and it is crucial for real-time systems. Hence, many filters with good performances in accuracy are limited in target tracking area due to their big computation. Here, computational complexity mainly denotes the times in terms of multiplications, divisions, additions, and subtraction for each run of an algorithm under no consideration of the process of generation, move, and measure for a target.

As described in Section 2, a state vector is assumed to be n-dimensional, and an observation vector is assumed to be m-dimensional, generally $m < n$. In addition, M is the number of fuzzy rules utilized as mentioned in Section 4.1. The computational procedure for FLRLSF mainly consists of three steps: the update of the state, covariance, and fading factor corresponding to Equations 23, 24, and
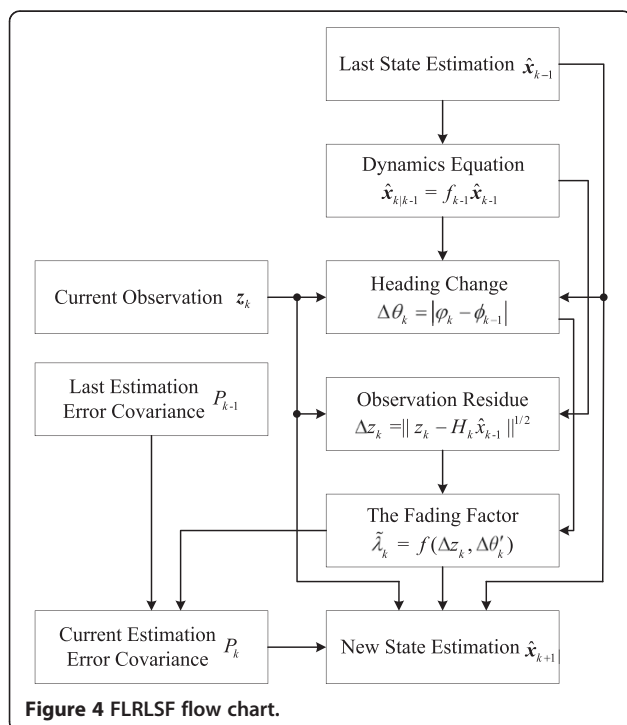
Table 2 Computational complexity for each filter

Filter	Computational complexity
RLSF	$14n^3 + (4m-1)n^2 + (12m^2 + 2m - 1)n + 2m^3 - m^2 + 4$
FLRLSF	$14n^3 + (4m-1)n^2 + (12m^2 + 2m - 1)n + 2m^3 - m^2 + 3M + 3$
Fα-βF	$2n^2 + (2m-1)n + 3M - 1$
HKF	$4n^3 + (12m+6)n^2 + (12m^2 + 2)n + 4m^3 + 2m^2 - 4m + 3M$

25, respectively. The computation of three steps is $(4m + 2)n^2 + (2m-1)n$, $14n^3 - 3n^2 + (12m^2 - 4m)n + 2m^3 - m^2 + 4$, and $3M - 1$, respectively. As a result, the computational complexity for FLRLSF is $14n^3 + (4m-1)n^2 + (12m^2 + 2m - 1)n + 2m^3 - m^2 + 3M + 3$. Similarly, the computational complexity for other three types of filters is shown in Table 2. Here, M is related to the number of fuzzy rules for each filter, generally different with one another. From Table 2, the order of computational complexity for four filters from small to large is Fα-βF, RLSF, FLRLSF, and HKF, respectively.

5 Experimental results and analysis

A stimulation experiment and a real test experiment have been carried out to evaluate the performance of the FLRLSF method in comparison with the other three existing methods, the traditional RLSF [18], FAα-βF [16], and HKF [14] for MTT.

5.1 Simulation experiment

In the simulation experiment, single radar is assumed to track a maneuvering target, and the following assumptions and the radar performance parameters are used. The radar initial position is located at (0 m, 0 m), and its performance parameters are as follows: the system transmission delay $\tau = 0$ s, sampling interval $T = 5$ s, range error $\sigma_r = 50$ m, and azimuth error $\sigma_\beta = 0.01°$. In the simulation scenario, the target moves in the air surveillance of 2-D Cartesian xy-plane according to the given
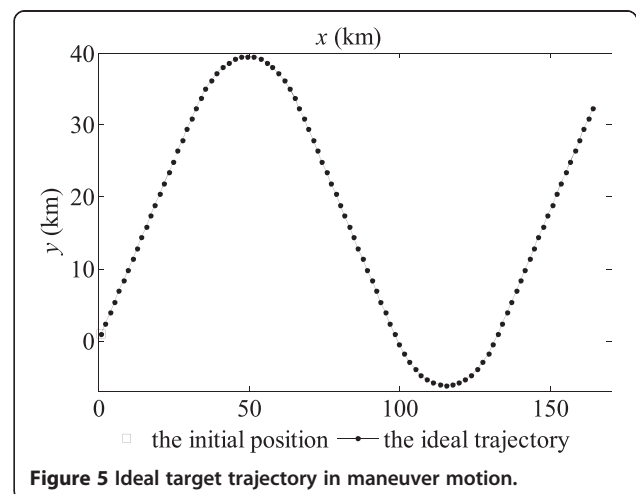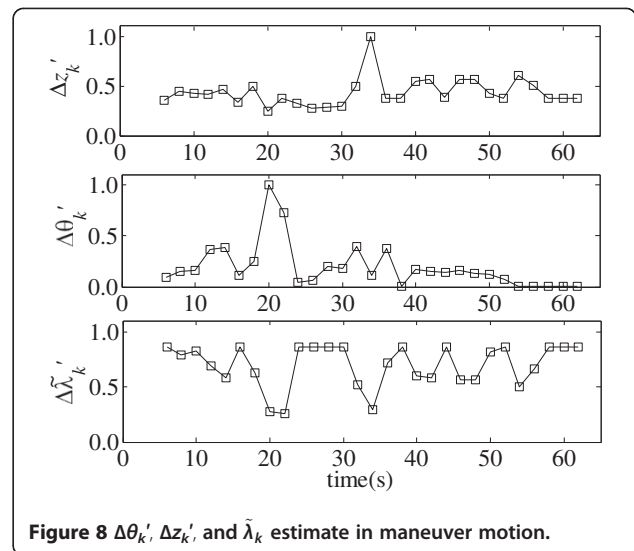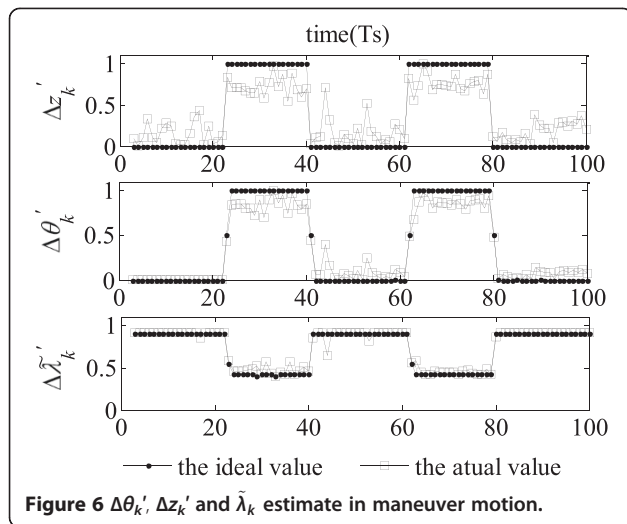

Figure 4 FLRLSF flow chart.

Figure 5 Ideal target trajectory in maneuver motion.

**Figure 6** $\Delta\theta_k'$, $\Delta z_k'$ and $\tilde{\lambda}_k$ estimate in maneuver motion.

Figure 8 $\Delta\theta_k'$, $\Delta z_k'$, and $\tilde{\lambda}_k$ estimate in maneuver motion.

trajectory below. Its initial state is given by $x_0 = [800$ m, 200 m/s, 900 m, 346 m/s]^T, and its trajectory is formed by 100 observations collected by the radar, which is divided into five phases: constant velocity motion, turn rate motion (0.2 rad/s), constant velocity motion, turn rate motion (–0.2 rad/s), and constant velocity motion, as shown in Figure 5. The turn rate model of the target motion is characterized by the following equation:

$$\boldsymbol{x}_k = \begin{bmatrix} 1 & \dfrac{\sin \omega_k T}{\omega_k} & 0 & -\dfrac{1-\cos \omega_k T}{\omega_k} \\ 0 & \cos \omega_k T & 0 & -\sin \omega_k T \\ 0 & \dfrac{1-\cos \omega_k T}{\omega_k} & 1 & \dfrac{\sin \omega_k T}{\omega_k} \\ 0 & \sin \omega_k T & 0 & \cos \omega_k T \end{bmatrix} \boldsymbol{x}_{k-1} + \boldsymbol{v}_k$$

(26)

where ω_k is the turn rate and $\boldsymbol{v}_k$ is the zero-mean white Gaussian noise with an unknown covariance. The simulation experiment is conducted by using a computer

with a dual-core CPU of Pentium 4 2.93 GHz, 1-GB RAM. The programs are performed by using the Matlab 2009a version software.

Figure 6 shows that the variational curves of $\Delta z_k'$, $\Delta\theta_k'$, and $\tilde{\lambda}_k$ are obtained according to the target motion in the ideal (noiseless) and noisy case, respectively. Figure 7 provides the root mean squared errors (RMSE) for the target positions using three methods for 100 Monte Carlo simulation runs. As can be shown from Figure 6, it is verified that the curves of $\Delta z_k'$ and $\Delta\theta_k'$ are able to reflect the maneuver changes exactly, and $\tilde{\lambda}_k$ can also be adjusted dynamically with their magnitudes by using the fuzzy system in this case. It can be seen from Figure 7 that the RMSE of FLRLSF is smaller than those of RLSF, FAα-βF, and HKF when the target moves at both constant velocity and turn rate, discussed as follows. Due to the perfect capability of FLRLSF to detect maneuver quickly and obtain its magnitude exactly, FLRLSF is able

Figure 7 Estimate errors for four filters.

Figure 9 True trajectory and tracking results.
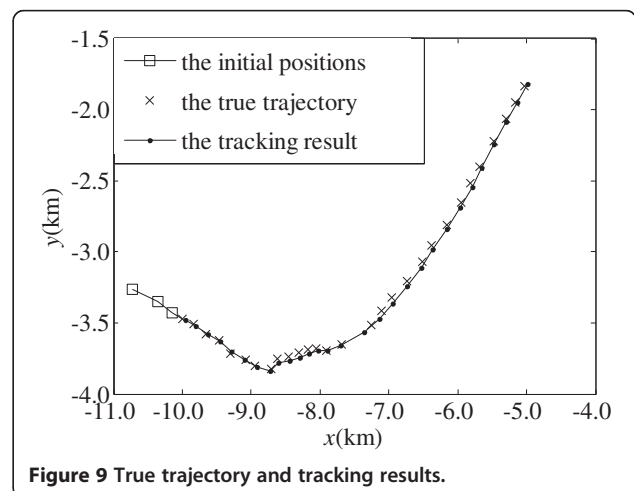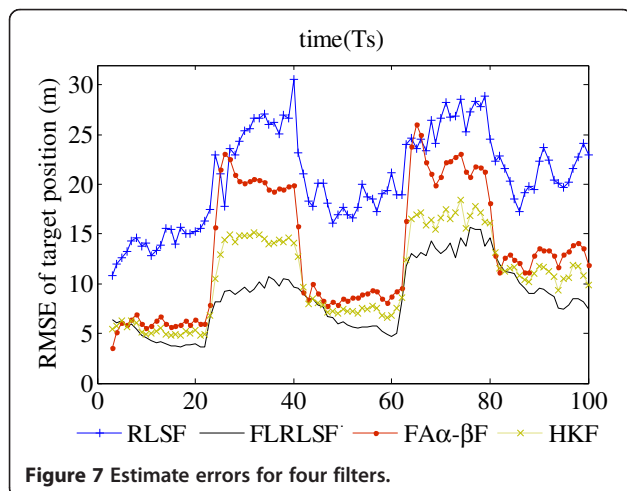
to estimate the target state timely and accurately. The average RMSE of the target positions by using FLRLSF, RLSF, FAα-βF, and HKF are 8.8, 21.8, 13.5, and 10.8 m respectively, and the corresponding average run time of CPU is 0.0089, 0.0083, 0.0047, and 0.0163 s. Hence, the results on average run time are consistent with the analysis for four filters in Section 4.3. Here, the average run time of FLRLSF is more than that of RLSF since the execution of the fuzzy system needs to consume a certain time. In addition, to compare with PF, the additional conditions are assumed to satisfy its run requirements [11]. The number of particles is given as 1,000. The average run time for PF is 0.8632 s, much longer than the four types of filters mentioned above.

5.2 Real test experiment

The real test experiment is evaluated by using real tracking data generated from some type of single radar. The radar performance parameters are represented as follows: the sampling interval $T = 2$ s, maximum detection range $r_{\max} = 21$ km, range error $\sigma_r = 20$ m, and azimuth error $\sigma_\beta = 0.5°$. The initial position of the target is $z_0 = [800$ m, 900 m$]^T$, and its trajectory is formed by 32 observations gathered by the radar. Figure 8 shows that the variational curves of $\Delta z_k'$, $\Delta \theta_k'$, and $\tilde{\lambda}_k$ are obtained according to the real tracking data. Figure 9 shows the real trajectory and the tracking results by using the proposed filter. The results in Figures 8 and 9 are analyzed below. Due to the rapid flight velocity, long flight time, and large azimuth error, the maneuver changes of the target are relatively complicated in the real test scenario. As can be known from Figure 8, $\tilde{\lambda}_k$ is able to estimate the maneuver magnitudes based on $\Delta z_k'$ and $\Delta \theta_k'$. Because of the capability of a triangular function to suppress noise of the inputs, the proposed filter is still able to detect maneuvers exactly by using the fuzzy system. As can be seen from Figure 9, FLRLSF is able to track the maneuvering target accurately in the real situation. As a result, it is verified that the proposed filter is feasible in real MTT.

6 Conclusion

In this paper, considering the properties and drawbacks of the traditional adaptive filters, FLRLSF is proposed for MTT in the situation of observations with unknown random characteristics. The paper employs the fading factor of RLSF to describe maneuver characteristics of the motion model, analyzes the relationship of the fading factor with observation residuals and heading changes, and maps the relationship into a set of fuzzy rules. By applying fuzzy logic in the standard RLSF and designing the fuzzy system, the fading factor is allowed to be adjusted adaptively based on the fuzzy rules. These rules

determine the fading factor dynamically according to the magnitudes of the observation residual and heading change in the current prediction. Therefore, FLRLSF is able to detect maneuvers timely and estimate their magnitude accurately. The effectiveness of the proposed filter is evaluated by using the simulation and real test experiment. Its performance in terms of tracking accuracy and the average run time is compared against those of RLSF, FAα-βF, and HKF. The results of the simulation experiment show that the proposed filter can track a maneuvering target adaptively, and it achieves better performance in tracking accuracy than the other three methods. In addition, the real test experiment validates its feasibility in real environment.

In future work, we will extend the proposed filter in tracking multiple targets in cluster in distributed multi-sensor system. Furthermore, we will also explore FLRLSF for the state estimates of global tracks after local track-to-local track fusion in the fusion center of the system.

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