Modular Fuzzy Interacting Multiple Model for Maneuvering Target Tracking

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ABSTRACT

A novel maneuvering target tracking algorithm is investigated. Drawing on the experience of combination idea of the modular structure and the fuzzy interacting multiple model algorithm (FIMM), a modular fuzzy interacting multiple model algorithm (MFIMM) is presented. The MFIMM algorithm consists of three independent modules working in parallel. The change of a target motion is also divided into three levels. The motion of a target is detected by a fuzzy control motion detector. Once the maneuver is detected, the MFIMM algorithm selects one of the three modules matching the actual movement of the target every moment. Afterwards, the MFIMM algorithm estimates the state of the target through interactive multiple model algorithm (IMM) based on square root unscented Kalman Filter (SRUKF) of the selected module. Therefore, the fuzzy motion detector deals with the level of motion and the modules switching, whereas the IMM-SRUKF accounts for the estimation of the dynamic system.

***Index Terms*—**maneuvering target tracking, MFIMM, IMM, SRUKF

1. INTRODUCTION

In many tracking systems, the target motion is modeled as a system whose varying state makes a transition according to an underlying model or several switching models. The selection of the proper model for applications of maneuvering target tracking is important and this problem has received much attention.

Many specific dynamic models of target motion have been developed for target tracking. The simplest model is constant-velocity (CV) models, or more precisely, "nearly-constant-velocity models", which is a non-maneuver model[1]. The white-noise acceleration model assumes that the target acceleration is an independent process (strictly white noise)[2].The Singer acceleration model[3] assumes the acceleration to be a time-correlated stochastic process and lays the foundation for several other effective maneuver models, such as the mean-adaptive acceleration model[4] and the asymmetrically distributed normal acceleration model[5]. Another common model is Jerk model[1], Jerk is the derivative of acceleration, which is the target acceleration that is chosen to be the descriptor of a target maneuver and modeled as a random process.

Each of the models described above performs well in specific scenarios, but there is no universally optimal model for all applications. The interacting multiple model (IMM) method[6] models the target motion as a hybrid system in which the state evolves according to a stochastic differential equation; the model jumps from one to another among a finite number of possible models according to a set of transition probabilities. The IMM algorithm constructed with many number of models provides good estimations when the models cover the types of motion well, but it reduces the effectiveness of the IMM due to the unnecessary competition between many non-matched models at any particular time[7]. Some modified IMM algorithms were presented for improving performance or computation efficiency in recent years. A variable structure MM (namely, VSMM) algorithm is proposed to solve the dilemma where the model set not only differs across targets but also varies with time forgiven targets[8][9]. The estimation with VSMM, however, depends on the auxiliary information (such as the terrain topography), which is hard to realize in some cases.

To solve the above problems, this paper proposes a modular fuzzy interacting multiple model algorithm (MFIMM): (1) The algorithm consists of three independent modules working in parallel, called non-maneuver, weak maneuver and strong maneuver respectively. Due to the independence of each modular, unnecessary competition between many non-matched models is reduced; (2) Using a novel fuzzy-control method selects proper module for maneuvering target according to the target motion situation, which decreases the detection delay; (3) Applying interacting multiple model algorithm in selected module avoids the problem of tracking error. The simulation results show that the algorithm can track maneuvering target effectively and improve the computational efficiency; In addition, the tracking accuracy of the proposed algorithm is better than that of IMM algorithm.

The paper is organized as follows. The problem is described in section 2. Section 3 provides modules structure. Section 4 presents fuzzy inference. Section 5 reviews the Interacting multiple model tracking algorithm. Section 6 proposed the modular fuzzy interacting multiple model tracking algorithm. The simulation results are showed to demonstrate the efficiency of the proposed methods in section 7. Section 8 concludes the paper.

2. PROBLEM DESCRIPTION

The system equations are usually described as follows:

$$X_{k+1} = f_k(X_k) + w_k \tag{1.a}$$

$$z_k = h_k(X_k) + v_k \tag{1.b}$$

In the equation, f_k and h_k denote the state transition matrix and the observation matrix, respectively. X is the target's state vector and z_k is the measurement vector. w_k and v_k are the system process noise and the measurement noise, respectively, assuming that their mean vectors are both zero and their variance matrixes are Q_k and R_k respectively.

3. MODULES STRUCTURE

Different tracking model is suitable for different scenarios. There is such a situation that some models may work well during constant-velocity tracking while other models may perform well during maneuver tracking. Aiming at the above situation, the modules division is put forward in this paper, including non-maneuver module, weak maneuver module and strong maneuver module respectively. Three modules perform in parallel and each of them contains different tracking models. Independence between different modules can remove the excessive competition from the unnecessary models.

3.1. Non-maneuver module

The non-maneuver module describes constant-velocity motion or nearly-constant-velocity motion by using CV model, which is the simplest case.

3.2. Weak maneuver module

Weak maneuvering target motion can be described by Singer model and the current statistical (CS) model. Singer model has a wide coverage from constant-velocity to constant-acceleration (CA) motion; CS model uses the current acceleration mean value as the input control in the one-step-ahead prediction equation for the algorithm, which makes the equation be the same as that of the CA model with the variance adaptively changed. Compared with the Singer model, CS model can more truly reflect the change of scope and strength when target maneuvers.

3.3. Strong maneuver module

Strong maneuver module includes Jerk model and its modified model. Jerk model estimates target acceleration rate and more suitable for highly maneuvering target tracking.

4. FUZZY INFERENCE

The change of a target motion is divided into three levels: no, small, and big. If the motion module that a target was in had been known at time $k-1$, it would be easy to select the module according to the level of motion changes at time k. Thus, the amount of calculation will be reduced and the tracking accuracy can be improved. Fuzzy theory uses relatively simple mathematical expressions to simulate the process of human thought and implements human control with computers, making complex systems deal with problems in accordance with people's way of thinking[10]. Therefore, we can use fuzzy theory to determine the motion mode of a target.

4.1. Motion detection based on fuzzy theory

Motion detection methods based on residual information are simple and easy to implement, therefore, they have been widely adopted. According to principles of the maneuvering target tracking, the actual motion mode of a target mismatches the non-maneuvering model when the target maneuvers. This will lead to increasing residuals, and tracking errors will increase accordingly. Taking into account the effect of random noises, the smoothing processing is carried out on the residual:

$$e(k) = \frac{1}{L}\sum_{i=k-L+1}^{k} \sqrt{e(i)' e(i)} \tag{2}$$

Where $e(k)$ is the residual at the moment k, and L is the smoothing length.

For a target, before the maneuvering occurs, the smoothed residual usually fluctuates around a fixed value randomly. It is a stable random process. However, when the target carries out maneuvering, the smoothed residual will no longer fluctuate steadily. It will increase all the way. In practical situations, when the residual is not large, but the residual variation between a moment and the next moment is large, the motion is also likely to change. The variation of the residual is as follows:

$$\Delta e(k) = e(k) - e(k-1) \tag{3}$$

First of all, carry out fuzzification on the input. The smoothed residual and its variation are used as the inputs of the fuzzy detector. After that, $e(k)$、$\Delta e(k)$ are fuzzified.

The fuzzy set of $e(k)$ is $\{PS, PM, PB\}$. The fuzzy set of $\Delta e(k)$ is $\{NB, ZO, PB\}$. Here, a trapezoid function is used as the membership function.

Next, design fuzzy rules. The Takagi-Sugeno fuzzy inference method does not require time-consuming and defuzzification operations which are difficult to analyze mathematically[11]. It also facilitates the establishment of fuzzy models of dynamic systems, meeting the requirements of real-time target tracking. Therefore, we use the Takagi-Sugeno method to build the inference rules which have two inputs and one output.

$$IF\ e(k) = A,\ \Delta e(k) = B,\ THEN\ P = C$$

Where A and B are fuzzy sets of $e(k)$、$\Delta e(k)$ respectively. C is the degree of occurrence of the motion changes, which is expressed as a percentage.

According to experts knowledge, no motion change will occur if C is in $[0, 0.35)$. Small motion changes, including transitions between the non-maneuver and weak maneuver modules and transitions between the weak maneuver and strong maneuver modules, will occur if C is in $[0.35, 0.75)$. Big motion changes, including transitions between the non-maneuver and strong maneuver modules, will occur if C is in $[0.75,1]$. The fuzzy rules are designed as follows:

$IF\ e(k) = PS,\ \Delta e(k) = NB,\ THEN\ P = 0;$

$IF\ e(k) = PS,\ \Delta e(k) = ZO,\ THEN\ P = 0.15;$

$IF\ e(k) = PS,\ \Delta e(k) = PB,\ THEN\ P = 0.35;$

$IF\ e(k) = PM,\ \Delta e(k) = NB,\ THEN\ P = 0.15;$

$IF\ e(k) = PM,\ \Delta e(k) = ZO,\ THEN\ P = 0.55;$

$IF\ e(k) = PM,\ \Delta e(k) = PB,\ THEN\ P = 0.75;$

$IF\ e(k) = PB,\ \Delta e(k) = NB,\ THEN\ P = 0.65;$

$IF\ e(k) = PB,\ \Delta e(k) = ZO,\ THEN\ P = 0.85;$

$IF\ e(k) = PB,\ \Delta e(k) = PB,\ THEN\ P = 1;$

The corresponding control table of fuzzy rules is showed as follows:

Table 1

$P(k)$		$\Delta e(k)$		
		NB	ZO	PB
$e(k)$	PS	0	0.15	0.35
	PM	0.15	0.55	0.75
	PB	0.65	0.85	1

4.2. State compensation

The motion status detection method described in the last section uses the smoothed residuals as the inputs of the detector, introducing the lag effect inevitably. The tracking performance will be affected if the status is not corrected.

Assume that the target is in a uniform motion at the initial moment. We use a CV model to do the tracking filtering. The maneuvering of the target occurs at the $k-d$ moment, while the detector detects the maneuvering at the moment k and changes the tracking module immediately. The filter uses the value at the $k-1$ moment as its initial value. However, between the $k-d$ moment and $k-1$ moment, we use the CV model to track the target after maneuvering. The model mismatches the actual movement, leading to increased errors. As a result, the initial unscented Kalman filter value at the moment k should be the state value X_{k-1}^{c} at the moment $k-1$ after correction.

Assume that the value at the $k-n$ moment is the optimal estimation. It is required that the $k-n$ moment occurs before the $k-d$ moment. Between the $k-n$ moment and $k-1$ moment, the corrected module is used to do the state estimation. In this way, the value at the $k-1$ moment will be the state value X_{k-1}^{c} after correction. The value at the $k-n$ moment is assumed to be the optimal estimation. Therefore, the $k-n$ moment may occur after the maneuvering if n is too small, and the amount of calculation will increase if n is too large. Generally, n should be larger than the smoothing length L.

Taking real-time performance and accuracy of the algorithm into account, the state compensation is only performed during transitions between the non-maneuver and strong-maneuver modules.

5. INTERACTING MULTIPLE MODEL TRACKIHNG ALGORITHM

The IMM estimator is a suboptimal hybrid filter that has been shown to be a useful hybrid state estimation schemes. The model of hybrid systems and IMM algorithms, initially proposed by Bloom, serves as a basis for the synthesis of more efficient filters for tracking maneuvering targets. Each cycle of IMM estimator consists of three major steps: interaction (mixing), filtering, and combination. The algorithm requires multiple filters, each corresponding to the target's acceleration state.

The IMM is applied based on square-root unscented Kalman filter (SRUKF) in the modular calculation. The model set selection will be illustrated in part 6.

6. THE MODULAR FUZZY INTERACTING MULTIPLE MODEL TRACKING ALGORITHM

Combining modular structure, fuzzy theory and interacting multiple model algorithm, a modular fuzzy interacting multiple model (MFIMM) algorithm is presented in target tracking. The MFIMM algorithm includes five fundamental steps:

Step1. The target motion detection

Using the module at time $k-1$ as the initial filter module calculates the probability C and motion state $S(k)$. If $S(k)=0$, motion at time k has no change, as same as motion at time $k-1$; If $S(k)=1$, motion at time k has a small change; If $S(k)=2$, motion at time k has a big change.

Step2. Select one module from module structure

If $S(k)=0$, the result of Step1 is the state estimation at time k. Go to step5.

If $S(k)=1$, a. the module at time $k-1$ is non-maneuver module, then the module at time k changes to weak maneuver module; b. the module at time $k-1$ is weak maneuver module, then the module at time k changes to strong maneuver module; c. the module at time $k-1$ is strong maneuver module, then the module at time k changes to weak maneuver module. Go to step4.

If $S(k)=2$, a. the module at time $k-1$ is non-maneuver module, then the module at time k changes to strong maneuver module; b. the module at time $k-1$ is strong maneuver module, then the module at time k changes to non-maneuver module.

Step 3: state compensation

Filtering module adopts the result of step2, and using the method of section 4.2 updates the state estimation X_{k-1}^{c} of time $k-1$ as the input at time k.

Step4: Estimation using IMM

With the initial value, estimation uses IMM algorithm based on SR- UKF.

Step5: Time $k+1$ go to step 1.

7. SIMULATION

The given algorithm is illustrated with one example of maneuvering target tracking. To simply the aerodynamic equation, Earth is assumed to be a non-rotating sphere and the trajectory is a target moving in the plane. Dynamic model with no lateral movement of a target is shown as follow:

$$\begin{bmatrix} \dot{v}_x \\ \dot{v}_y \end{bmatrix} = \frac{\rho VS}{2m} \begin{bmatrix} -C_x v_x - C_y v_y \\ C_y v_x - C_x v_y \end{bmatrix} + \frac{g_0 r_0^2}{r^3} \begin{bmatrix} x - R_{0x} \\ y - R_{0y} \end{bmatrix} \quad (4)$$

In the equation, ρ is air density under the standard atmosphere model; V is the velocity; S is reference area of the target; m is the quality of spacecraft; C_x, C_y are drag coefficient and lift coefficient, respectively; g_0 is gravity acceleration; R_0 is radius of the earth; R_{ox}, R_{oy} are coordinates of spacecraft in relative coordinate system; R_0 is geocentric distance.

S, m, C_x and C_y are parameters published by Qualcomm[16]; longitude, latitude, altitude and course heading of launch point are $0^\circ, 0^\circ, 0m, 90^\circ$; longitude, latitude, altitude of targets are $0^\circ, 0^\circ, 66km$; initial Mach number is 10; inclination angle is -1°; declination angle is 0°; control quantum is impact angle, which is the constant 15°.The trajectory is got through 4-order Runge-Kutta and is shown as follows:

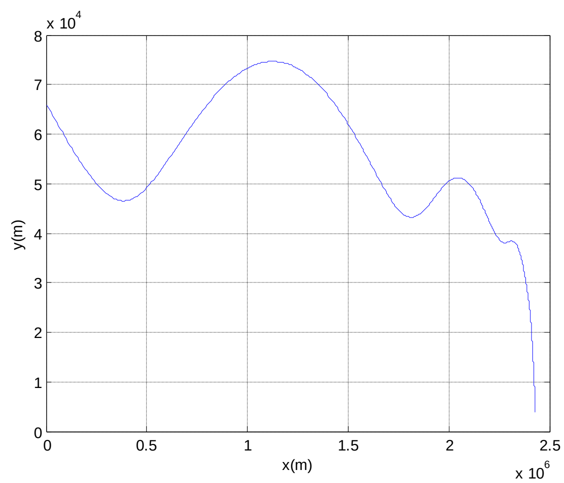

Figure 1 the trajectory of target

The proposed algorithm includes three modules: non-maneuver module with CV model, weak maneuver module with Singer model and CS model, strong maneuver module with Jerk model. The sampling period T is 1 s, the standard covariance of models' process noise is $\sigma = 2m/s$, the standard deviation of measurement noise is $\sigma_x = \sigma_y = 50m/s$, and the matrix of the probabilities is

$$P = \begin{bmatrix} 0.7 & 0.3 \\ 0.2 & 0.8 \end{bmatrix}$$

The RMSEs of IMM and MFIMM are demonstrated in Figure 2. During the first 750s, MFIMM algorithm has better performance than IMM, especially when the target maneuvering. With the same initial conditions, the simulation time of MFIMM is about a half that of IMM. But in the last period of time, the tracking accuracy of MFIMM is not very good, especially at the direction of y. That is because the position changes so fast that exceeds the thresholds of $e(k)$ and $\Delta e(k)$, which improve the level of motion and then lead to modules switch abnormally. If the more accurate thresholds were found, the MFIMM algorithm could be more widely used. In addition, the proposed algorithm is a viable algorithm to other tracking methods.

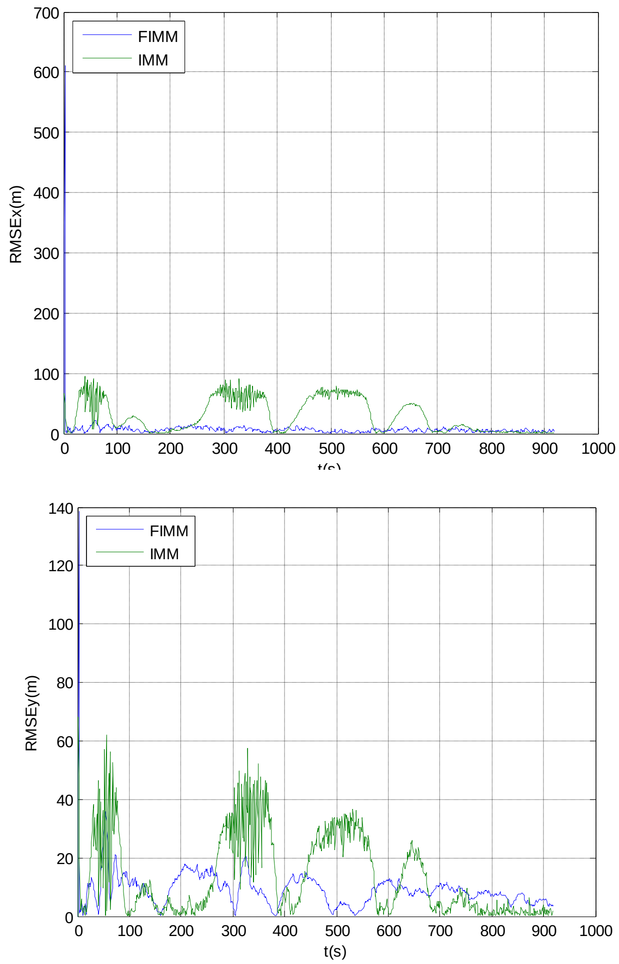

Figure 2 position RMSEs for IMM and MFIMM

8. CONCLUSION

The MFIMM algorithm contains independent modules, which are IMM filters performing in parallel. Then the modules are selected according to a fuzzy control method. The presented algorithm inherits the merit of the IMM methods. The MFIMM algorithm improves performance of maneuvering target tracking by avoiding the excessive competition from the unnecessary models. And then it reduces computation burden effectively. For the future study, we are focusing on finding a more accurate boundary of the thresholds of $e(k)$ and $\Delta e(k)$ in the specific problems.

9. ACKNOWLEDGEMENTS

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