

Maneuvering target tracking using threshold interacting multiple model algorithm

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Abstract: To avoid missing track caused by the target maneuvers in automatic target tracking system, a new maneuvering target tracking technique called threshold interacting multiple model (TIMM) is proposed. This algorithm is based on the interacting multiple model (IMM) method and applies a threshold controller to improve tracking accuracy. It is also applicable to other advanced algorithms of IMM. In this research, we also compare the position and velocity root mean square (RMS) errors of TIMM and IMM algorithms with two different examples. Simulation results show that the TIMM algorithm is superior to the traditional IMM algorithm in estimation accuracy.

Key words: maneuvering target tracking; Kalman filter; interacting multiple model (IMM); threshold interacting multiple model (TIMM)

The main function of the radar processor is to execute the tracking program. Since the computing speed of current computers is improved greatly, most tracking filters are based on the Kalman filter. Recently, there have been many advances in sensor technology to reduce measurement noise^[1]. However, there are no devices that can detect the man-made maneuvers by sensors themselves. Even a short-term acceleration will result in a bias in the state estimate if only the standard Kalman filter is applied to track the target. During the past two decades, many algorithms based on the Kalman filter for tracking maneuvering targets have been suggested.

With the input estimate (IE) method in Refs. [2, 3], the acceleration can be estimated by the least square error technique and applied to update the Kalman filter. But this algorithm requires heavy computing load and can lead to delay in acceleration estimate. Another algorithm called variable dimension filter (VDF)^[4] introduces extra components in a state model when a maneuver is detected and comes back to a quiescent state model when it disappears. This algorithm may give rise to discontinuity problems because of switching between two state models. Many advanced algorithms based on or combining the two methods above have been brought forward such as MVDIE^[5], EVDF^[6]. However,

they do not radically overcome defects such as heavy computing loads or discontinuity problem.

The interacting multiple model (IMM) algorithm proposed by Blom et al.^[7,8] can track a maneuvering target steadily. With this method, each model is assigned different accelerations to deal with tracking a maneuvering target. The probability of each model being true is found by using a likelihood function for the model. Movement between the models is performed using a transition probability. This algorithm has better results than the IE and VDF algorithms because a smooth transition is achieved from one model to others. But it obtains larger errors before the acceleration starts than traditional methods. Furthermore, it must increase the number of models to get better performance. Some ameliorating IMM algorithms are suggested to get better performance or reduce complexity such as Refs. [9 – 11]. In this research we propose another approach called threshold-IMM (TIMM). First we just add thresholds and do not change the internal structure of IMM so that it can be applied to not only the IMM algorithm but also to ameliorating IMM algorithms. In our approach, compared to classical IMM, it can reduce errors in great part before the acceleration onset. It can also improve maneuvering tracking performance.

1 Interacting Multiple Model Tracking

1.1 Maneuvering target model

A possible model of IMM models is described by the linear discrete time-invariant state equation:

$$X(k+1) = FX(k) + G_1 U(k) + G_2 V(k) \quad (1)$$

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where $\mathbf{X}(k) = \{x(k), \dot{x}(k), y(k), \dot{y}(k)\}^T$ is the state vector in the two-dimensional plane, $\mathbf{U}(k) = \{u_x(k), u_y(k)\}^T$ are the input acceleration components, \mathbf{F} is the state transition matrix, \mathbf{G}_1 is the coupling matrix for maneuver inputs, \mathbf{G}_2 is the process noise input matrix, and $\mathbf{V}(k)$ is the process noise. They are given as follows (T is the sampling time interval):

$$\mathbf{F} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{G}_1 = \mathbf{G}_2 = \begin{bmatrix} \frac{T^2}{2} & 0 \\ T & 0 \\ 0 & \frac{T^2}{2} \\ 0 & T \end{bmatrix} \quad (2)$$

And the measurement equation is

$$\mathbf{Z}(k) = \mathbf{H}\mathbf{X}(k) + \mathbf{W}(k), \quad \mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (3)$$

where $\mathbf{Z}(k)$ is the radar measurement vector, \mathbf{H} is the model output matrix, and $\mathbf{W}(k)$ is the measurement noise. It is assumed to be an uncorrelated white Gaussian noise sequence with zero means. Each model of IMM/TIMM assumes different input accelerations.

1.2 IMM tracking filter

Fig. 1 shows the architecture of a classical IMM tracking filter^[8]. It consists of a Kalman filter for each model, a model probability evaluator, state estimate and covariance combiner. Furthermore, each Kalman filter makes use of a mixed estimate as input.

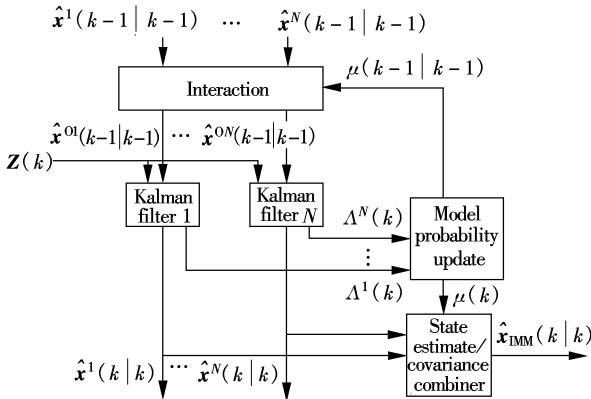


Fig. 1 Architecture of the classical IMM tracking filter

One step of the classical IMM algorithm is presented as follows:

The mixing weights (probability) represent that model μ_i was in effect at time $k-1$ when μ_j is in effect at time k conditioned on the measurement history up to time $k-1$, denoted by $\mathbf{Z}(k-1)$. It is deduced as

$$\mu_{i|j}(k-1) \triangleq \mathbf{P}\{\mathbf{M}_i(k-1) | \mathbf{M}_j(k), \mathbf{Z}^{k-1}\} = \frac{1}{\bar{c}_j} P_{ij} \mu_i(k-1) \quad (4)$$

where P_{ij} is the assumed model transition probability and the normalization constant \bar{c}_j is denoted as

$$\bar{c}_j = \sum_{i=1}^N P_{ij} \mu_i(k-1) \quad (5)$$

The mixed estimate and covariance for the filter associated with model M_j is given by

$$\begin{aligned} \hat{\mathbf{x}}^{Oj}(k-1 | k-1) &= \sum_{i=1}^N \hat{\mathbf{x}}^i(k-1 | k-1) \mu_{i|j}(k-1 | k-1) \\ \mathbf{P}^{Oj}(k-1 | k-1) &= \sum_{i=1}^N \mu_{i|j}(k-1 | k-1) \{\mathbf{P}^i(k-1 | k-1) + [\hat{\mathbf{x}}^i(k-1 | k-1) - \hat{\mathbf{x}}^{Oj}(k-1 | k-1)] \times [\hat{\mathbf{x}}^i(k-1 | k-1) - \hat{\mathbf{x}}^{Oj}(k-1 | k-1)]^T\} \end{aligned} \quad (6)$$

The outputs of the filter model j are computed via the standard Kalman filter equations using the mixed estimate (6) and the covariance (7). The likelihood functions which match to the filter model j at time k are given by

$$\Lambda_j = \mathbf{P}[z(k) | M_j(k), z^{k-1}] = N[\tilde{z}(k); 0, s_j(k)] \quad (8)$$

where $\tilde{z}(k)$ is the measurement prediction error, $s_j(k)$ is the measurement prediction covariance, and N stands for the two-dimensional normal school.

Thirdly, the posterior probability of the model j is updated as

$$\mu_j(k) \triangleq \mathbf{P}[M_j(k) | \mathbf{Z}^k] = \frac{\Lambda_j \bar{c}_j}{c} \quad (9)$$

where

$$c = \sum_{j=1}^N \Lambda_j \bar{c}_j \quad (10)$$

Finally, for output only, the state estimate and covariance are yielded as

$$\hat{\mathbf{x}}_{\text{IMM}}(k | k) = \sum_{j=1}^N \hat{\mathbf{x}}^j(k | k) \mu_j(k) \quad (11)$$

$$\mathbf{P}_{\text{IMM}}(k | k) = \sum_{j=1}^N \mu_j(k) \{\mathbf{P}^j(k | k) + [\hat{\mathbf{x}}^j(k | k) - \hat{\mathbf{x}}_{\text{IMM}}(k | k)] \times [\hat{\mathbf{x}}^j(k | k) - \hat{\mathbf{x}}_{\text{IMM}}(k | k)]^T\} \quad (12)$$

2 Threshold Interacting Multiple Model Algorithm

The architecture of the TIMM tracking filter proposed in this paper is illustrated in Fig. 2. It is composed of a classical IMM filter, some Kalman filters, and a threshold controller. The additional Kalman filters have the same number and parameters as the classical IMM filter. They are computed in parallel and use the same input state estimate and covariance in each circle. The threshold controller is applied to choose the output of which filter (additional Kalman filters or the classical IMM filter) can be used as the output of TIMM. They will be described in details as follows.

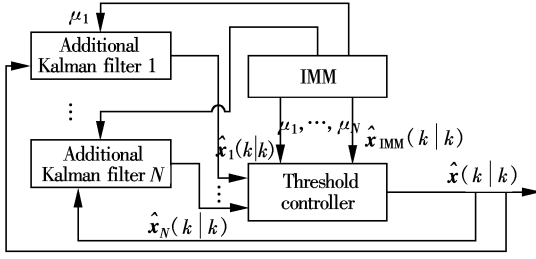


Fig. 2 Architecture of TIMM tracking filter

2.1 Additional Kalman filters

According to the maneuvering target model above, each additional Kalman filter has different input acceleration components the same as the IMM internal Kalman filter and receives the same measurement sequence $\{z(k)\}$, $k=1, 2, 3, \dots$, to get the minimum mean sequence error (MMSE) and fast convergence by recursive performance. The input state estimate and covariance of each additional Kalman filter are decided by the threshold controller. The one-step predicted state and its covariance of additional filter j is given by

$$\left. \begin{aligned} \mathbf{x}_j(k|k-1) &= \mathbf{F}\hat{\mathbf{x}}_j(k-1|k-1) + \mathbf{G}_1 u_j(k-1) & \mu_j \geq \theta \\ \mathbf{x}_j(k|k-1) &= \hat{\mathbf{x}}_{\text{IMM}}(k|k-1) & \mu_{1,2,\dots,N} < \theta \end{aligned} \right\} \quad (13)$$

$$\left. \begin{aligned} \mathbf{P}_j(k|k-1) &= \mathbf{F}\mathbf{P}_j(k-1|k-1)\mathbf{F}^T + \mathbf{G}_1\mathbf{Q}_j\mathbf{G}_1^T & \mu_j \geq \theta \\ \mathbf{P}_j(k|k-1) &= \mathbf{P}_{\text{IMM}}(k|k-1) & \mu_{1,2,\dots,N} < \theta \end{aligned} \right\} \quad (14)$$

where μ_j is the output of the classical IMM filter mentioned above, and θ is the threshold yield by the threshold controller. It will be presented in the next part.

2.2 Threshold controller

With the classical IMM algorithm, the situation when mismatch maneuvering target models of the classical IMM algorithm are in effect will reduce the tracking accuracy. For example, in section 3 of Ref. [8], Bar-Shalom obtained the result that compared with Ref. [3]. The errors of the IMM algorithm before acceleration onset are larger. So we apply the threshold controller to quantify weightings ($\mu_j(k)$) of output just like analog digital conversion. Each model probability will be compared with the threshold which is yielded by the threshold controller. If the probability of the model j is larger than the threshold, the output of the additional Kalman filter j will be used as the output of TIMM. If no model probability is larger than the threshold, the output of the IMM algorithm will be used as the output of TIMM. The difficulty of this algorithm is how to choose the threshold values. They can be decided by experience equations. We recommend an experience equation as follows:

$$\theta = \lambda/N \quad \lambda \geq 1 \quad (15)$$

where λ is the expansion constant and it is always more than 1, and N is the number of Kalman filters referred to above.

3 Simulation Results

In this section, simulation results are reported to compare the performance of the TIMM algorithm with the IMM algorithm by different experiments. In the experiments of this paper, the following assumptions and parameter values are used. The sampling time interval is assumed to be 10 s, which is the time of a radar antenna scanning a revolution. The standard deviation of measurements for each coordinate is 100 m. The IMM2 algorithm^[8] (It is composed of two Kalman models) and its threshold IMM algorithm are applied. Each simulation consists of 100 Monte Carlo runs.

Experiment 1 The target scenario used in Ref. [2] and Ref. [4] is modified for simulation testing here. The initial state for the target is $(\dot{x}, \dot{y}) = (0.1 \text{ m}, 43.3 \text{ m/s}, 0.1 \text{ m}, 25 \text{ m/s})$ and with a constant speed until it reaches $t = 400 \text{ s}$. Then it starts to maneuver with the acceleration of $(u_x, u_y) = (-0.6 \text{ m/s}^2, -0.2 \text{ m/s}^2)$. It completes at $t = 600 \text{ s}$ and the other maneuver starts at $t = 610 \text{ s}$ with an acceleration of $(u_x, u_y) = (3 \text{ m/s}^2, 2 \text{ m/s}^2)$ for 50 s. We make the trajectory of the target with a sharp left turn for 200 s and then a sharp right turn for 50 s.

The comparison of position RMS errors (only for coordinate x) for the IMM and TIMM is shown in Fig. 3. It can be inferred from this figure that compared with IMM, the position errors of TIMM can be reduced in great part before the acceleration onset. The position errors of TIMM after the acceleration onset can also be reduced in the mass. Fig. 4 is the plot of velocity RMS errors of each algorithm. The results indicate that TIMM has a better performance of velocity detections whether the maneuver occurs or not.

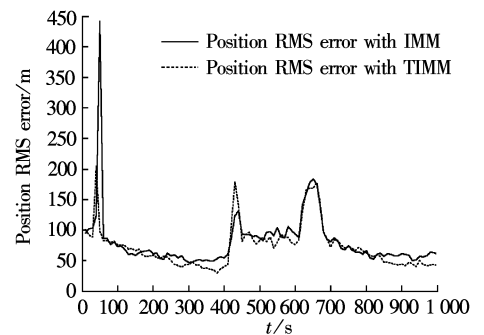


Fig. 3 Position RMS error

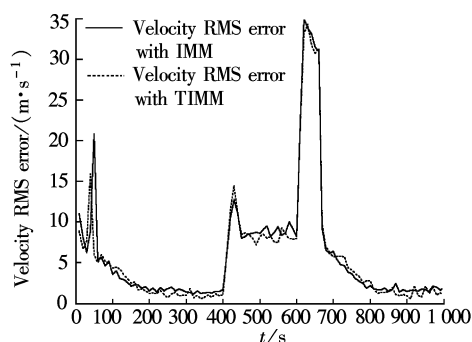


Fig. 4 Velocity RMS error

Experiment 2 In this experiment, the target scenario considered in Ref. [12] is used for simulation. The initial position of the target is $(x, y) = (5\,000\text{ m}, 4\,000\text{ m})$ apart from radar site (as zero point) with an initial speed of $(v_x, v_y) = (38\text{ m/s}, 38\text{ m/s})$. The target is assumed to start a sharp left turn with the acceleration $(u_x, u_y) = (-1.3\text{ m/s}^2, -3.0\text{ m/s}^2)$ at time 470 s for 3 scans. At time 500 s it undergoes another maneuver with acceleration $(u_x, u_y) = (-1.9\text{ m/s}^2, -3.3\text{ m/s}^2)$ for 2 scans. A Monte Carlo simulation is performed for IMM and TIMM algorithms. Fig. 5 and Fig. 6 are the plots of RMS errors of position and velocity (only for the coordinate x).

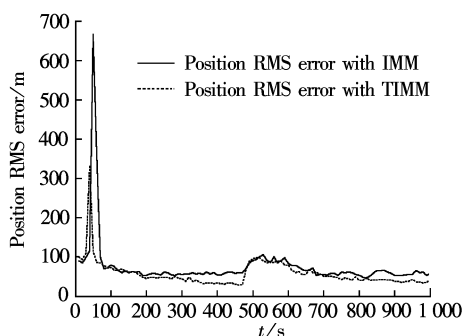


Fig. 5 Position RMS error

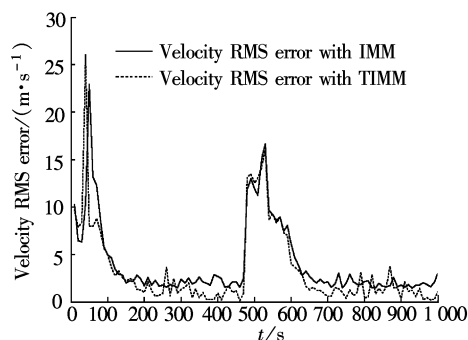


Fig. 6 Velocity RMS error

From the results of Fig. 5 and Fig. 6, we can compare the performance of IMM and TIMM algorithms. It is clear that both the position and velocity can be reduced nearly 50% before the maneuver onsets if the TIMM algorithm is used instead of the tra-

ditional IMM algorithm. It is also inferred from these figures that after the maneuver onsets, the position errors of the TIMM algorithm are a little smaller than the IMM algorithm. From the results of Fig. 3 and Fig. 5, the performance of the TIMM algorithm used in different magnitudes of maneuver value can be compared. The higher/lower the accelerations are, the larger/smaller the TIMM algorithm will take from the RMS errors of the traditional IMM algorithm.

4 Conclusion

In this paper, an ameliorating IMM algorithm called TIMM for the maneuvering target tracking is proposed. It is shown from the simulation results that the TIMM algorithm can perform much better than the traditional IMM algorithm of Ref. [8]. Furthermore, because it does not change the internal structure of IMM, it can be applied to other ameliorating IMM algorithms and improve their performance. However, it requires more computational load than the traditional IMM algorithm of Ref. [8]. Future work will focus on reducing the computational load of the TIMM algorithm. This algorithm will be highly applicable for tracking maneuvering targets.

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机动目标跟踪的 TIMM 算法

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摘要:针对如何避免或减少由于目标的机动运动所带来的估计误差问题,提出了具有门限的相互作用多模型估计 (TIMM) 的新算法. 该算法主要应用于雷达目标自动跟踪系统中. TIMM 算法在相互作用多模型估计器 (IMM) 算法的基础上引入门限控制器来提高跟踪精度, 该算法同样适用于其他各种改进的 IMM 算法. 通过 2 个不同的例子, 对由 TIMM 和 IMM 这 2 种算法产生的均方根误差进行比较. 仿真结果表明, 同 IMM 算法相比较, TIMM 算法可减少估计误差, 从而提高机动目标的跟踪性能.

关键词:机动目标跟踪; 卡尔曼滤波器; 相互作用多模型估计器; 具有门限的相互作用多模型估计器

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