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A Switched IMM Estimator based on the Model Probability Cumulant

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Abstract

Taking into account the disadvantage of the potential loss of accuracy due to the overmodeling at these nonmaneuvering times in the interacting multiple model (IMM) method, an improved IMM algorithm based on the Viterbi technique and the model probability cumulant is proposed. First, select one or two optimal models from the model set to enhance the model utilization rate. Then, judge the variation of the target motion state according to the maneuvering detection mechanism based on the model probability cumulant, and finally switch the different IMM methods. Simulation results show that the proposed method has an enhanced performance in tracking a maneuvering target.

Keywords: *maneuvering target tracking, interacting multiple model (IMM), viterbi technique, model probability cumulant*

1. Introduction

The interacting MM (IMM) algorithm [1] is a popular suboptimal method for the maneuvering target tracking, where multiple models with different structures or processing noise levels are used to describe the target motion and the final estimate is obtained by a weighted sum of the estimates from every filter of the different models. Nevertheless, It has the drawbacks of an unnecessary amount of computations when the target is not maneuvering and the potential loss of accuracy due to the overmodeling at these nonmaneuvering times. For this problem, the reweighted IMM (RIMM) method proposed in [2] is based on the incorporation of the alternating expectation condition maximization method into the IMM method. Although it can enhance the performance of the IMM method, its weight calculations is more complicated with high computational load. Variable structure MM (VSMM) method [3] can decrease the computational cost and avoid the potential loss of accuracy. However, this method need some priori information to select an admissible model set at any given time. Recently, the extended Viterbi IMM (IMM-EV) algorithm is proposed in [4], which have an improved performance for a maneuvering target tracking with moderate computational cost. However, the selection of the number of the optimal model will decide the performance of the IMM-EV algorithm, and the number is hard to be determined without some prior information.

To solve the aforementioned problem, an improved IMM algorithm based on the IMM-EV method is proposed in this letter. Firstly, the optimal model is selected in the model set according to the Viterbi technique. Then, judge the variation of the target motion state according to the maneuvering detection mechanism based on the model probability cumulant, and finally switch the different IMM methods. Simulation results show that the proposed method has an enhanced performance in tracking a maneuvering target.

2. Extended Viterbi IMM Method

Extended Viterbi (EV) algorithm is a dynamic programming algorithm, which is used to solve the decoding problem of the hidden Markov model by forward iteration. Recently, this method has been widely used in the fields of target tracking, data association and

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communication [4-8]. In order to select the optimal model among the model set of the IMM method, extended Viterbi technique is combined with the IMM algorithm, referred to as IMM-EV algorithm in [4]. The steps are simply described as follows.

Given n models, and an integer m with $1 \le m \le n$. Let the initial model probability be $\mu_0(j) = \eta_j$, $0 \le \eta_j \le 1$, $j = 1,...,n$, and $\sum_{j=1}^{n} \eta_j = 1$. Assume $\hat{\mathbf{x}}_0^j$ and $\mathbf{P}_0^j$ are known.

Step 1: Calculate mixing probability.

$$\mu_{k-1}(l_{sj} \mid j) = \frac{\max^{(s)}_{1 \le i \le n}\{p_{ij}\mu_{k-1}(i)\}}{\sum_{s=1}^{m} \max^{(s)}_{1 \le i \le n}\{p_{ij}\mu_{k-1}(i)\}}, \quad j = 1,...,n,\ s = 1,...,m \tag{1}$$

Where $l_{sj} = \arg\{\max^{(s)}_{1 \le i \le n}\{p_{ij}\mu_{k-1}(i)\}\}$.

Step 2: Input interacting.

$$\hat{\mathbf{x}}_{k-1}^{0j} = \sum_{s=1}^{m} \hat{\mathbf{x}}_{k-1}^{l_{sj}} \mu_{k-1}(l_{sj} \mid j) \tag{2}$$

$$\mathbf{P}_{k-1}^{0j} = \sum_{s=1}^{m} \mu_{k-1}(l_{sj} \mid j)\{\mathbf{P}_{k-1}^{l_{sj}} + [\hat{\mathbf{x}}_{k-1}^{l_{sj}} - \hat{\mathbf{x}}_{k-1}^{0j}][\hat{\mathbf{x}}_{k-1}^{l_{sj}} - \hat{\mathbf{x}}_{k-1}^{0j}]^{\mathrm{T}}\} \tag{3}$$

Step 3: Parallel filter. Mixed state estimates $\hat{\mathbf{x}}_{k-1}^{0j}$ and state error covariance matrices $\mathbf{P}_{k-1}^{0j}$ are used to calculate predicted state $\hat{\mathbf{x}}_{k|k-1}^{j}$ and covariance $\mathbf{P}_{k|k-1}^{j}$ matched the model M_k^j. Then calculate the update state $\hat{\mathbf{x}}_{k|k-1}^{j}$ and covariance $\mathbf{P}_{k|k-1}^{j}$, respectively.

Step 4: Calculate model probability.

$$\mu_k(j) = \frac{\Lambda_k(j)\sum_{s=1}^{m} \max\limits_{1 \le i \le n}^{(s)}\{p_{ij}\mu_{k-1}(i)\}}{\sum_{j=1}^{n} \Lambda_k(j)\sum_{s=1}^{m} \max\limits_{1 \le i \le n}^{(s)}\{p_{ij}\mu_{k-1}(i)\}} \tag{4}$$

Where $\Lambda_k(j) = N[\mathbf{v}_k^j; 0, \mathbf{S}_k^j]$ is the likelihood function. $\mathbf{v}_k^j = \mathbf{z}_k - \mathbf{H}_k^j \hat{\mathbf{x}}_{k|k-1}^j$ is the innovation with zero mean and covariance S_k^j. Extended Kalman filter (EKF) [9] is employed to achieve the passive maneuvering target tracking in this letter.

Step 5: Calculate the mixture probability of the m best models.

$$\tilde{\mu}_k(\tilde{l}_r) = \frac{\max^{(r)}_{1 \le j \le n}\{\mu_k(j)\}}{\sum_{r=1}^{m} \max^{(r)}_{1 \le j \le n}\{\mu_k(j)\}}, r = 1,...,m$$

Where:

$\tilde{l}_r = \arg\{\max^{(r)}_{1 \le j \le n}\{\mu_k(j)\}\}$.

Step 6: Output interacting. i.e., $\hat{\mathbf{x}}_k = \sum_{r=1}^{m} \tilde{\mu}_k(\tilde{l}_r)\hat{\mathbf{x}}_k^{\tilde{l}_r}$.

Remarks. In the IMM-EV algorithm, we define the IMM-EV1 ($m = 1$) and the IMM-EV2 ($m = 2$) algorithms by the different value of m. The difference of these two methods is that the IMM-EV1 method has a better performance in tracking an uniform motion target, and its performance will decrease seriously when tracks a maneuvering target. While the IMM-EV2 has a better performance in tracking a maneuvering target, its performance will decline seriously and inferior to the IMM-EV1 method when tracks a uniform motion target. In summary, the IMM-EV1 method is more suitable for an uniform motion target tracking, while the IMM-EV2 method is more suitable for a maneuvering target tracking.

3. Improved IMM-EV Algorithm

To solve the aforementioned problem, we propose an improved IMM-EV algorithm, referred to as switched IMM-EV (SIMM-EV) algorithm based on a new maneuvering detection mechanism. The proposed method can switch the IMM-EV1 method and IMM-EV2 method correctly, i.e., implement the IMM-EV1 method when the target takes an uniform motion, otherwise, implement the IMM-EV2 algorithm.

As known, model probability reflects the real motion feature of the maneuvering target in the IMM filtering. The model probability will change markedly when the target motion mode changes, and there will be a short-term model transition. But several intervals later, the model probability will tend to a stable value. In order to accurately determine the real motion mode of the maneuvering target, define the model probability cumulant as:

$$\Phi_d(\alpha,k)=\sum_{i=k-d+1}^{k}\mu(i)\alpha^{k-i} \tag{5}$$

Where $\mu(i)$ denotes the model probability which plays a main role at time i, α denotes the decay factor with $0<\alpha<1$, and d denotes the number of the time interval. As can be seen in Equation (5), multi-scan model probabilities are considered, which are used to avoid the incorrect judgement of the real motion mode due to the sudden change of a single-scan model probability.

The variation of the model probability cumulant between the L intervals is defined as:

$$\Delta\Phi_L=|\Phi_d(\alpha,k-L)-\Phi_d(\alpha,k)| \tag{6}$$

Where L is a given constant, and it is an integer time of the sampling period.

If $\Delta\Phi_L>\varepsilon$, we can determine that the motion mode of the target changes in the time interval $[k-L,\ k]$ and the minimum of l can be further computed according to Equation (7). Then the time $k-l$ can be considered as the accurate change time of the motion mode.

$$|\Phi_d(\alpha,k-l)-\Phi_d(\alpha,k)|>\varepsilon,\ \ 1\le l\le L \tag{7}$$

The steps of the proposed algorithm are described as follows:

Step 1: Initialization. Set the initial parameters α, d, L and the initial model probability μ_0;

Step 2: Implement the IMM-EV1 method, and the EKF method [7] is employed for the passive tracking system;

Step 3: Calculate the model probability cumulant of the model playing a main role according to Equation (6), and judge whether the target motion mode makes a change;

Step 4: If the target motion mode remain unchanged, keep the previous filter method, and go up to step 3. Otherwise, go to step 5;

Step 5*:* Calculate the accurate change time $k-l$ of the motion mode according to Equation (7);

Step 6: Judge the change of the target motion mode. If the motion mode change from the uniform motion to a maneuvering motion, initialize the parameters in IMM-EV2 method and implement this method from the time $k-l$. Otherwise, initialize the parameters in IMM-EV1 and implement this method from the time $k-l$. Modify the estimated states between the time $k-l$ and k, go up to step 3.

4. Simulations

To verify the effectiveness of the proposed algorithm, referred to as SIMM-EV algorithm, consider a single maneuvering target tracking example by a multiple passive tracking system, and compare the proposed algorithm SIMM-EV with the IMM, IMM-EV1 and IMM-EV2 algorithms.

Assume that the initial state of a target is $\mathbf{x}_0$=[1900m 0m/s 0m/s^2 10000m -150m/s 0m/s^2]^T, and the target takes a uniform motion in the first 25 seconds. Then starts to take uniform accelerated motions with the acceleration (a_x, a_y)=(5, 5) m/s^2 and (a_x, a_y)=(-15, -10) m/s^2, lasting 21 seconds and 8 seconds, respectively. Finally, the target takes a uniform motion. In this simulation, the sampling period is $T = 1s$, sampling 100 times in all.

In the tracking scenario, three models are employed, one constant velocity (CV) model with standard error $\sigma_{\mathbf{w}}$ =5m of process noise and two constant acceleration (CA) models with standard error $\sigma_{\mathbf{w}1}$ =5m and $\sigma_{\mathbf{w}2}$ =50m of process noise. The measurements are obtained from three fixed bearing-only sensors which located at (1000-4000)m, (5000-2000)m, and (5000-11000)m, respectively. The measurement equation is described as $\mathbf{z}_k^i = h_{m_k}(\mathbf{x}_k) + \mathbf{v}_k^i$, where $\mathbf{z}_k^i$ denotes the measurement of the i th sensor. $h_{m_k}(\mathbf{x}_k) = \arctan\left(\dfrac{y_k - y_{S_i}}{x_k - x_{S_i}}\right)$ denotes the measurement function with m_k =1, 2, 3. $\mathbf{v}_k^i$ denotes the measurement noise of the i th sensor, and $\mathbf{v}_k^j \sim N(0, \sigma_{\mathbf{v}}^2)$. $\mathbf{w}_k$ and $\mathbf{v}_k^i$ are unrelated with each other. Set the standard error of the measurement noise as $\sigma_{\mathbf{v}} = 1\text{mrad}$. Let the length of the smooth window (the number of the time interval) be $d = 8$, and decay factor be $\alpha = 0.8$, $L = 5$. 100 Monte Carlo runs are performed. The initial model probability is $\boldsymbol{\mu}_0$ =[0.8, 0.1, 0.1], and the model transition probability is:

$$\mathbf{P} = \begin{bmatrix} 0.90 & 0.05 & 0.05 \\ 0.05 & 0.90 & 0.05 \\ 0.05 & 0.05 & 0.90 \end{bmatrix}$$

Figure 1 shows the comparison of the position RMSE of the four algorithms, it is clear that the SIMM-EV algorithm has the similar accuracy to the IMM-EV1 when the target takes a uniform motion among the time intervals [1s, 25s] and [53s, 100s], and the accuracy is higher than the IMM-EV2 algorithm. When the target takes a maneuvering motion among the time intervals [26s, 52s], the SIMM-EV algorithm has the similar accuracy to the IMM and IMM-EV2 methods, and has a higher accuracy than the IMM-EV1 method. The reason is that the proposed algorithm can adaptively switch the IMM-EV1 and the IMM-EV2 methods, the IMM-EV1 method plays a important role when the target takes a uniform motion, otherwise, the IMM-EV2 method will be performed to tracking the maneuvering target. Moreover, we can also conclude that the tracking accuracy of the IMM-EV2 method is slightly higher than the IMM method, because the IMM-EV2 method includes the optimal model selection operator which can reduce the competition among the models. Although the IMM-EV1 has a better performance when the target takes a uniform motion, its performance will decline seriously when the maneuver occurred to the target.

Figure 2 shows the comparison of the velocity RMSE of the four algorithms. Table 1 illustrates the comparison of the accuracy of the four algorithm at different time intervals. We can also conclude that the proposed algorithm can switch the IMM-EV1 and IMM-EV2 method effectively, and has a better performance than the other methods.

Figure 3-6 show the model probabilities of the four algorithms. As can be seen, the SIMM-EV algorithm has the same model probability to the IMM-EV1 method at the two uniform motion stages, and to the IMM-EV2 at the maneuvering motion state. It is indicate that the proposed algorithm can adaptively switch the two methods. However, the proposed algorithm has a little disadvantage, it is that the model switched time is slightly deviation to the real time of the maneuver occurred.

Table 2 illustrates the comparison of the average run-time of each simulation. It is clear that the computational cost of the SIMM-EV algorithm is slightly higher than the IMM-EV1 and IMM-EV2 methods due to the switch step of the two methods. The IMM method has the lowest computational cost. Table 3 shows the accuracy comparison of the four algorithms under the different measurement noises. As can be seen that the position RMSE increase with the increase of the measurement noise, but the SIMM-EV algorithm is superior to the other three methods, which shows that the proposed has a better performance than the other methods in tracking a maneuvering target.

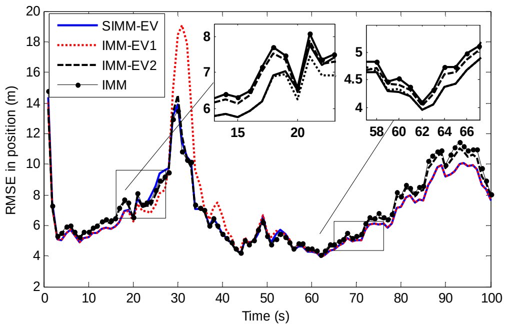

Figure 1. Position RMSE

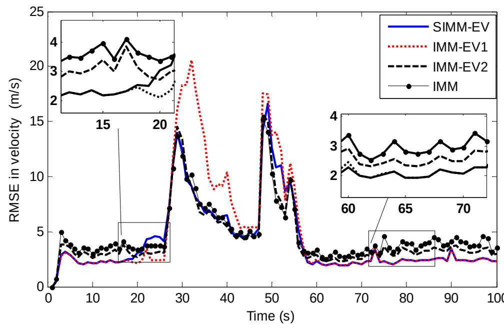

Figure 2. Velocity RMSE

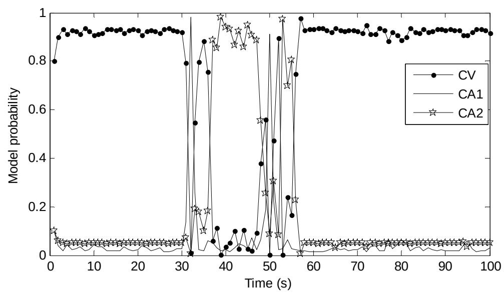

Figure 3. Model Probability of IMM-EV1

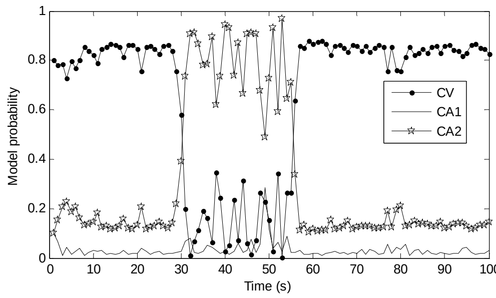

Figure 4. Model Probability of IMM-EV2

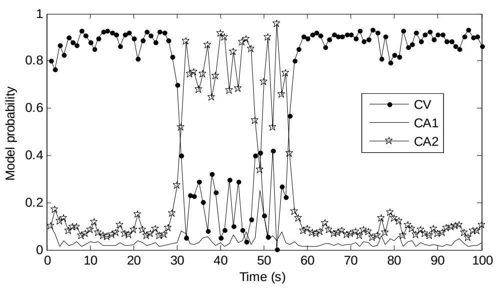

Figure 5. Model Probability of IMM

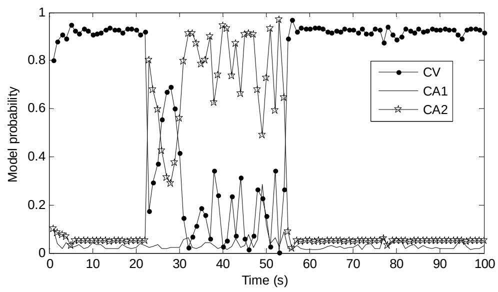

Figure 6. Model Probability of SIMM-EV

Table 1. Average RMSE of the Position at Different Motion Stage (m)

Algorithm	Uniform (1~25s)	Accelerate (26~52s)	Uniform (53~100s)
IMM	8.6317	10.8997	8.1077
IMM-EV1	7.9242	12.7317	7.5884
IMM-EV2	8.4341	10.8079	7.9532
SIMM-EV	7.9398	10.6607	7.5337

Table 2. Average Run-time.

Algorithm	IMM	IMM-EV1	IMM-EV2	SIMM-EV
Run-time (s)	0.0624	0.0645	0.0687	0.0868

Table 3. Average RMSE of the Position under Different Measurement Noise (m)

	Measurement noise (mrad)					
	0.7	0.8	0.9	1	2	3
IMM	6.5728	7.3854	8.0829	8.9925	16.9221	23.5160
IMM-EV1	6.6283	7.4527	8.1373	9.0710	16.9309	24.2351
IMM-EV2	6.4908	7.2990	7.9483	8.8442	16.5125	22.9338
SIMM-EV	6.3752	7.0893	7.6300	8.4745	15.4020	20.9784

5. Conclusion

In this letter, in order to improve the performance of the IMM algorithm, the Viterbi technique is used to solve the overmodeling problem at the nonmaneuvering times. We proposed a SIMM-EV algorithm, which can switch the IMM-EV1 and IMM-EV2 methods correctly according to the maneuvering detection mechanism based on the model probability cumulant. Simulation results show that the proposed method has an enhanced performance in tracking a maneuvering target.

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References

[1] HAP Blom, Y Bar-Shalom. The Interacting Multiple Model Algorithm for Systems with Markovian Switching Coefficient. *IEEE Trans. on Automatic Control*. 1988; 33(8): 780-783.
[2] LA Johnston, V Krishnamurthy. An Improvement to The Interacting Multiple Model (IMM) Algorithm. *IEEE Trans. on Signal Processing*. 2001; 49(12): 2909-2923.
[3] XR Li. Multiple-model Estimation with Variable Structure Part II: Model-set Adaptation. *IEEE Trans. Automatic Control*. 2000; 45: 2047-2060.
[4] TJ Ho, B Chen. Novel Extended Viterbi-Based Multiple-Model Algorithms for State Estimation of Discrete-Time Systems with Markov Jump Parameters. *IEEE Trans. on Signal Processing*. 2006; 54(2): 393-404.
[5] TJ Ho. *Switched IMM-EV Algorithms for State Estimation of Some Jump Markov Systems*. Proceedings of the 17th World Congress, International Federation of Automatic Control, Seoul, Korea. 2008; 1396-1401.
[6] Xiuling He, Yan Shi, Jiang Yunfang. Improved Based on "Self-Adaptive Turning Rate" Model Algorithm. *TELKOMNIKA Indonesian Journal of Electrical Engineering.* 2013; 11(6): 45-50.
[7] TJ Ho. A Switched IMM-Extended Viterbi Estimator-Based Algorithm for Maneuvering Target Tracking. *Automatica.* 2011; 47(1): 92-98.
[8] Leela Kumari, B Padma Raju K. Performance Evaluation of Unscented Kalman Filter for Gaussian/non-Gaussian Tracking Application. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 3(1): 93-101.
[9] M Boutayeb, D Aubry. A strong Tracking Extended Kalman Observer for Nonlinear Discrete-time Systems. *IEEE Trans. on Automatic Control*. 1999; 44(8): 1550-1556.