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Shipborne radar maneuvering target tracking based on the variable structure adaptive grid interacting multiple model*

Zheng-wei ZHU

(*School of Information Engineering, Southwest University of Science and Technology, Mianyang 621010, China*)

E-mail: zhuzwin@163.com

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Abstract: The trajectory of a shipborne radar target has a certain complexity, randomness, and diversity. Tracking a strong maneuvering target timely, accurately, and effectively is a key technology for a shipborne radar tracking system. Combining a variable structure interacting multiple model with an adaptive grid algorithm, we present a variable structure adaptive grid interacting multiple model maneuvering target tracking method. Tracking experiments are performed using the proposed method for five maneuvering targets, including a uniform motion - uniform acceleration motion target, a uniform acceleration motion - uniform motion target, a serpentine locomotion target, and two variable acceleration motion targets. Experimental results show that the target position, velocity, and acceleration tracking errors for the five typical target trajectories are small. The method has high tracking precision, good stability, and flexible adaptability.

Key words: Shipborne radar, Target tracking, Variable structure, Interacting multiple model, Adaptive grid algorithm
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1 Introduction

In recent years the performances of anti-ship missiles including speed, maneuverability, and stealth have been greatly improved. Specifically, at the terminal attack stage, anti-ship missiles usually have strong maneuvering characteristics such as high speed, multi-mode, high frequency, and large amplitude. All these raise higher demands for the response speed and tracking accuracy of shipborne radar systems. Traditional target tracking algorithms cannot meet all these demands. It is thus necessary to propose a strong maneuvering target tracking algorithm with good tracking adaptability to various maneuvering targets.

For decades, many research findings have been obtained in the field of maneuvering target localization and tracking (Blom and Bar-Shalom, 1988; Li and Bar-Shalom, 1993; Munir and Atherton, 1995; Li *et al*., 2006; Peng, 2007; Zhang and Chen, 2010; Messaoudi *et al*., 2010; Foo and Ng, 2011; Ge *et al*., 2011; Zhang *et al*., 2012). Current research is focused mainly on the multiple model method, which is generally thought to be the best method for maneuvering target tracking (Magill, 1965; Blom and Bar-Shalom, 1988; Li and Bar-Shalom, 1993; Munir and Atherton, 1995; Xu *et al*., 2003; Zhu, 2008; Liu *et al*., 2009; Foo and Ng, 2011; Yuan and Zheng, 2011). The original multiple model algorithm, proposed by Magill (1965), uses a fixed number of models; the filters corresponding to the models work in parallel and their outputs are fused. There is, however, no interaction between the models; thus, the algorithm is not applicable for targets with a variety of maneuvering modes. Blom and Bar-Shalom (1988) extended the original multiple model algorithm and proposed the interacting multiple model (IMM) algorithm. The advent of the IMM algorithm is considered as a milestone in the development of multiple model algorithms. It is the first algorithm that has sufficient cost-effectiveness and can be applied to many actual estimation

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problems with variable structures or parameters. The main characteristics of the IMM algorithm are that: there are interactions between the models; the transitions between the target motion models are taken into account; and the target motion models are assumed to be a Markov or semi-Markov process.

The first- and second-generation multiple model algorithms both use a fixed model set; that is, they are fixed structure multiple model (FSMM) algorithms. For a target whose maneuvering modes are unknown, however, it is impossible to use a small model set to cover the overall target maneuvering models. Increase in the number of models would lead to great increase in the computational complexity and the tracking time. Moreover, using more models may not necessarily improve the performance of the algorithms. Due to the limitations of FSMM algorithms, they need to be improved in practical applications. Li and Bar-Shalom (1993) proposed a variable structure multiple model (VSMM) algorithm. The algorithm adopts a time-varying model set instead of the fixed model set in FSMM algorithms. Munir and Atherton (1995) proposed an adaptive interacting multiple model (AIMM) algorithm. The algorithm does not need to predefine the sub-models, but it needs to predefine and estimate the target acceleration according to the target motion characteristics; the correctness of the estimated acceleration significantly impacts the performance of maneuvering target tracking.

To solve the above-mentioned problems, we propose a variable structure adaptive grid interacting multiple model tracking method by combining the variable structure interactive multiple model with adaptive grid technology. Tracking experiments were conducted on five typical maneuvering target trajectories to evaluate its tracking performance.

2 Variable structure interacting multiple model

The model set of the standard IMM algorithm is fixed, and requires a transition probability matrix to control the possibility of switching between the models. This determines its limitations: (1) If the model set adopted and the real model set do not exactly match at a certain time, e.g., only a smaller or simplified model set is used when the original model set is very large or very complex, the FSMM estimator will not be optimal. (2) At any time k+1, the system model set N_{k+1} generally relies on the hybrid state of the current system. For a specific system model, it can be switched only to the system model for which the transition probability is not equal to zero. However, in practice, the model transition probability generally depends on the base state of the system. In addition, in maneuvering target tracking, the process noise coefficient is a major model parameter that needs to be considered. Usually when a target takes a non-maneuvering motion, we may use a small noise to approximately represent the interference of the external environment, but when a target takes a maneuvering motion, a large noise should be used. In the IMM algorithm, we adopt a larger noise to represent the non-maneuvering of a target, which can improve the real-time performance of the system. When designing the noise coefficient of a maneuvering target model, we need to select a reasonable level of noise according to the expected maneuvering amplitude and the maneuvering model number of the target.

To avoid the limitations of the FSMM algorithm, and based on the VSMM algorithm presented by Li and Bar-Shalom (1993), we propose an improved VSMM algorithm. The proposed algorithm is improved by using a posteriori information in filtering. By adjusting the Markov transition probability matrix in filtering, the Markov parameters of the algorithm will be adaptive for a posteriori information. In addition, a model base matching function module is increased and the best model set can be selected according to the matching information.

Suppose N_k is the model set that the IMM algorithm uses at time k and N is the whole model set (namely N is the union set of all the N_k's). The optimal VSMM estimator in conditional mean sense is

$$\hat{\boldsymbol{x}}(k/k)=\sum_{N_k}\hat{\boldsymbol{x}}_{k|k}^{N_k}P\{N_k \mid z^k\}, \tag{1}$$

$$P(k/k)=\sum_{N_k}\Big[P_{k|k}^{N_k}+(\hat{\boldsymbol{x}}(k/k)-\hat{\boldsymbol{x}}_{k|k}^{N_k}) \cdot(\hat{\boldsymbol{x}}(k/k)-\hat{\boldsymbol{x}}_{k|k}^{N_k})^{\mathrm{T}}\Big]P\{N_k \mid z^k\}, \tag{2}$$

where $P\{N_k \mid z^k\} \triangleq P\{n_k \in N_k \mid z^k\}$ is a posteriori probability that the effective model sequence n_k belongs to N_k, and N_k is a compatibility model set sequence at time k. $\hat{\boldsymbol{x}}_{k|k}^{N_k}$ and $P_{k|k}^{N_k}$ are the optimal estimates and the optimal variance assuming $n_k \in N_k$, respectively:

$$\hat{\boldsymbol{x}}_{k|k}^{N_k} = \sum_{n_k \in N_k} \hat{\boldsymbol{x}}_{k|k}^{N_k} P\{n_k \mid N_k, z^k\}, \tag{3}$$

$$P_{k|k}^{N_k} = \sum_{n_k \in N_k} \left[P_{k|k}^{n_k} + (\hat{\boldsymbol{x}}_{k|k}^{N_k} - \hat{\boldsymbol{x}}_{k|k}^{n_k})(\hat{\boldsymbol{x}}_{k|k}^{N_k} - \hat{\boldsymbol{x}}_{k|k}^{n_k})^{\mathrm{T}} \right] \cdot P\{n_k \mid N_k, z^k\}, \tag{4}$$

where $\hat{\boldsymbol{x}}_{k|k}^{n_k}$ is the optimal estimate at time k assuming that the real model sequence is n_k, and $P_{k|k}^{n_k}$ is the corresponding variance.

It can be seen from the above analysis that, the optimal variable structure interacting multiple model (VSIMM) estimate is the probability-weighted sum of the overall estimates which are based on the compatibility model set sequences that do not contain or intersect with each other.

Fig. 1 is the principle block diagram of the VSIMM algorithm. Compared with the standard IMM algorithm, the VSIMM algorithm has a model base matching function module. The mode base matching is composed mainly of two function modules, namely the model set adaptive (MSA) module and the model set sequence conditional probability estimation (MCPE) module. The MSA module is used to determine which model set to use in the multiple model algorithm at each time, namely determining the candidate model sets and selecting the best model set from the candidate model sets. In the MSA module both a priori knowledge and a posteriori information in the measurement sequence are needed. An adaptive grid method is adopted for adaptively processing the model set in this study. The basic idea is that, given a rough grid, the parameter space grids of possible system models are recursively and adaptively adjusted according to the target state estimates, model probabilities, likelihood functions, and measurement residuals. In addition, the model set sequences at the present moment and the previous or next moment are usually different in the VSIMM algorithm. If the model set sequence at the present moment does not contain a certain model of the model set sequence at the previous moment, then the model needs to be reactivated. The MCPE will set an initial probability for the newly activated model; an initial state estimate and an initial error variance will also be given to the sub-filter that is corresponding to the newly activated model.

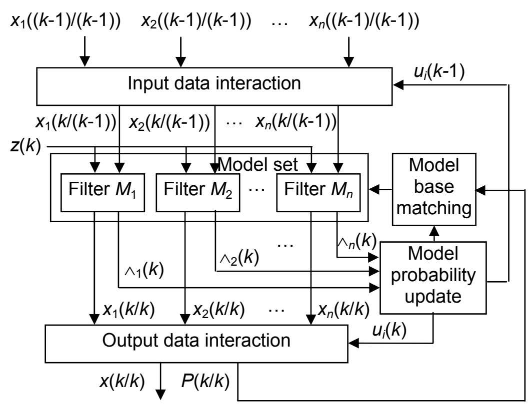

Fig. 1 Principle block diagram of the variable structure interacting multiple model (VSIMM) algorithm

3 Adaptive grid algorithm

Different from the fixed grid IMM algorithm, the interacting models in the adaptive grid IMM algorithm are adaptively selected according to the chosen parameters; i.e., in the continuous interval, the interacting models are selectively determined according to the transition probabilities, the model switching probabilities, and so on.

Assume that the real turning speed of the maneuvering target at the present moment is unknown, but in the continuous interval $[-\omega_{\max}, \omega_{\max}]$. Construct a time-varying IMM algorithm with N models; the model set at time k is $M_k=\{\omega_k^{\mathrm{L}}, \omega_k^2, \ldots, \omega_k^C, \ldots, \omega_k^{N-1}, \omega_k^{\mathrm{R}}\}$, where $-\omega_{\max} \le \omega_k^{\mathrm{L}} \le \omega_k^2 \le \ldots \le \omega_k^C \le \ldots \le \omega_k^{N-1} \le \omega_k^{\mathrm{R}} \le \omega_{\max}$. Assume that the initial model set of the algorithm is $M_0=\{\omega_0^{\mathrm{L}}=-\omega_{\max}, \omega_0^2=0, \ldots, \omega_0^C=0, \ldots, \omega_0^{N-1}=0, \omega_k^{\mathrm{R}}=\omega_{\max}\}$. The turning speed from time k to time $k+1$ is adjusted using two parameters, grid center and grid distance.

The grid center is adjusted according to

$$\omega_{k+1}^{C}=\mu_k^{\mathrm{L}}\omega_k^{\mathrm{L}}+\mu_k^2\omega_k^2+\cdots+\mu_k^C\omega_k^C+\cdots+\mu_k^{N-1}\omega_k^{N-1}+\mu_k^{\mathrm{R}}\omega_k^{\mathrm{R}}, \tag{5}$$

where μ_k^i is the posterior probability of the ith model at time k.

The grid distance is adjusted in accordance with the following rules:

When $\mu_k^C=\max\{\mu_k^{\mathrm{L}}, \mu_k^2, \ldots, \mu_k^C, \ldots, \mu_k^{N-1}, \mu_k^{\mathrm{R}}\}$, there is no switch between the models:

$$\begin{cases}\omega_{k+1}^{\mathrm{L}}=\begin{cases}\omega_{k+1}^{C}-\lambda_k^{\mathrm{L}}/2, & \mu_k^{\mathrm{L}}<\tau_1,\\ \omega_{k+1}^{C}-\lambda_k^{\mathrm{L}}, & \text{otherwise},\end{cases}\\ \omega_{k+1}^{\mathrm{R}}=\begin{cases}\omega_{k+1}^{C}+\lambda_k^{\mathrm{R}}/2, & \mu_k^{\mathrm{R}}<\tau_1,\\ \omega_{k+1}^{C}+\lambda_k^{\mathrm{R}}, & \text{otherwise},\end{cases}\end{cases} \tag{6}$$

where $\lambda_k^{\mathrm{L}}=\max\{\omega_k^C-\omega_k^{\mathrm{L}},\ \delta_w\}$, $\lambda_k^{\mathrm{R}}=\max\{\omega_k^C-\omega_k^{\mathrm{R}},\ \delta_{\mathrm{w}}\}$, $\tau_1=0.05$ is a threshold used for detecting impossible models, and δ_{w} is a model interval, which is a design parameter.

When $\mu_k^{\mathrm{L}}=\max\{\mu_k^{\mathrm{L}}, \mu_k^2, \ldots, \mu_k^C, \ldots, \mu_k^{N-1}, \mu_k^{\mathrm{R}}\}$, switch to the left:

$$\begin{cases}\omega_{k+1}^{\mathrm{L}}=\begin{cases}\omega_{k+1}^{C}-2\lambda_k^{\mathrm{L}}, & \mu_k^{\mathrm{L}}>\tau_2,\\ \omega_{k+1}^{C}-\lambda_k^{\mathrm{L}}, & \text{otherwise},\end{cases}\\ \omega_{k+1}^{\mathrm{R}}=\omega_{k+1}^{C}+\lambda_k^{\mathrm{R}},\end{cases} \tag{7}$$

where $\tau_2=0.95$ is a threshold used for detecting important models.

When $\mu_k^{\mathrm{R}}=\max\{\mu_k^{\mathrm{L}}, \mu_k^2, \ldots, \mu_k^C, \ldots, \mu_k^{N-1}, \mu_k^{\mathrm{R}}\}$, switch to the right:

$$\begin{cases}\omega_{k+1}^{\mathrm{L}}=\omega_{k+1}^{C}-\lambda_k^{\mathrm{L}},\\ \omega_{k+1}^{\mathrm{R}}=\begin{cases}\omega_{k+1}^{C}+2\lambda_k^{\mathrm{R}}, & \mu_k^{\mathrm{R}}>\tau_2,\\ \omega_{k+1}^{C}+\lambda_k^{\mathrm{R}}, & \text{otherwise}.\end{cases}\end{cases} \tag{8}$$

Set a transition probability for the model set at time k, $M_k=\{\omega_k^{\mathrm{L}}, \omega_k^2, \ldots, \omega_k^C, \ldots, \omega_k^{N-1}, \omega_k^{\mathrm{R}}\}$, and the new model set at time k+1, $M_{k+1}=\{\omega_k^{\mathrm{L}'}, \omega_k^{2'}, \ldots, \omega_k^{C'}, \ldots, \omega_k^{(N-1)'}, \omega_k^{\mathrm{R}'}\}$, and use a recursive adaptive method to realize the interactions between the model sets. Then the transition probability matrix may be expressed as

$$\boldsymbol{P}_{k,k+1}=\begin{bmatrix}\boldsymbol{P}_{\mathrm{LL}'} & \boldsymbol{P}_{\mathrm{L}2'} & \cdots & \boldsymbol{P}_{\mathrm{L}C'} & \cdots & \boldsymbol{P}_{\mathrm{L}(N-1)'} & \boldsymbol{P}_{\mathrm{LR}'}\\ \boldsymbol{P}_{2\mathrm{L}'} & \boldsymbol{P}_{22'} & \cdots & \boldsymbol{P}_{2C'} & \cdots & \boldsymbol{P}_{2(N-1)'} & \boldsymbol{P}_{2\mathrm{R}'}\\ \vdots & \vdots & & \vdots & & \vdots & \vdots\\ \boldsymbol{P}_{C\mathrm{L}'} & \boldsymbol{P}_{C2'} & \cdots & \boldsymbol{P}_{CC'} & \cdots & \boldsymbol{P}_{C(N-1)'} & \boldsymbol{P}_{C,\mathrm{R}'}\\ \vdots & \vdots & & \vdots & & \vdots & \vdots\\ \boldsymbol{P}_{(N-1)\mathrm{L}'} & \boldsymbol{P}_{(N-1)2'} & \cdots & \boldsymbol{P}_{(N-1)C'} & \cdots & \boldsymbol{P}_{(N-1)(N-1)'} & \boldsymbol{P}_{(N-1)\mathrm{R}'}\\ \boldsymbol{P}_{\mathrm{RL}'} & \boldsymbol{P}_{\mathrm{R}2'} & \cdots & \boldsymbol{P}_{\mathrm{R}C'} & \cdots & \boldsymbol{P}_{\mathrm{R}(N-1)'} & \boldsymbol{P}_{\mathrm{R,R}'}\end{bmatrix},$$

where $\boldsymbol{P}_{ij}$ is the covariance matrix consisting of the optimal estimates.

4 Experimental results and analysis

To analyze and assess the tracking performance and adaptability of the variable structure adaptive grid IMM tracking algorithm proposed in this study for the maneuvering targets, we have performed tracking experiments for five typical target trajectories.

4.1 Trajectory 1: uniform acceleration - uniform motion

The target moves first at a uniform acceleration, and then at a uniform speed. The initial state of the target is x_0={0 m, 0 m/s, 20 m/s^2}, the total running time is 200 s, and other relevant motion parameters are as shown in Table 1. The target motion trajectory is as shown in Fig. 2a.

Table 1 Relevant motion parameters of trajectory 1

Time (s)	Acceleration (m/s^2)
0–40	20
40–200	0

For the uniform acceleration - uniform motion target shown in Fig. 2a, the tracking results of the target motion trajectory, velocity, and acceleration in the x-direction are shown in Figs. 2a, 2b, and 2c, respectively, and the root mean square errors (RMSEs) of the target position, velocity, and acceleration tracking are shown in Fig. 2d.

Trajectory 1 (Fig. 2a) corresponds to a motion that the target maneuvers moderately. The estimates of the target trajectory (position) are basically coincident with the real values of the target trajectory; the estimates of the target speed fluctuate in the vicinity

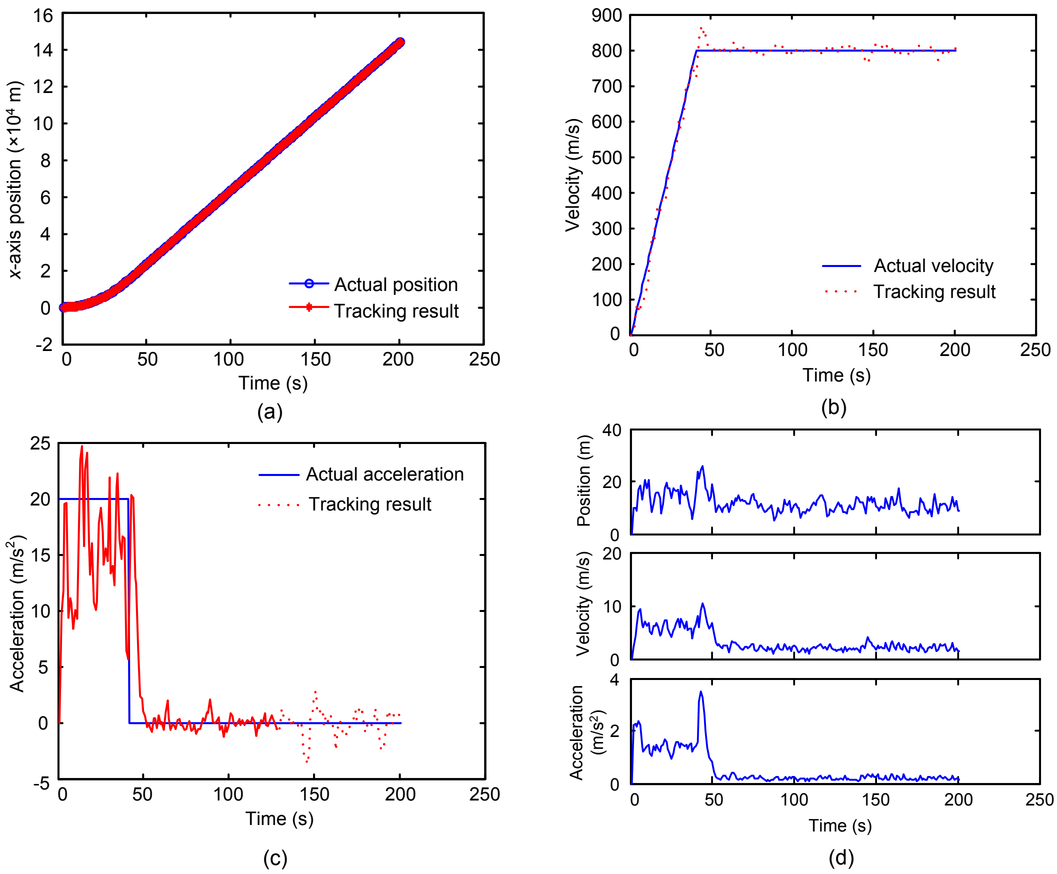

Fig. 2 Tracking results of the uniform acceleration - uniform motion target

(a) Target trajectory 1 and its tracking result; (b) Target velocity and its tracking result; (c) Target acceleration and its tracking result; (d) RMSE of target position, velocity, and acceleration tracking

of the true values of the target speed, but the fluctuation frequency is low and the fluctuation range is also small; the estimation errors of target acceleration are a little large during the acceleration phase, but small during the uniform motion phase. Overall, for the uniform acceleration - uniform motion target, the proposed variable structure adaptive grid IMM algorithm can accurately track the target.

4.2 Trajectory 2: uniform motion - uniform acceleration motion

The target moves first at a uniform speed, and then at a uniform acceleration. The initial state of the target is x_0={0 m, 20 m/s, 0 m/s^2}, the total running time is 200 s, and other relevant motion parameters are as shown in Table 2. The target motion trajectory is as shown in Fig. 3a.

For the uniform motion - uniform acceleration motion target shown in Fig. 3a, the tracking results of the target motion trajectory, velocity, and acceleration in the x-direction are shown in Figs. 3a, 3b, and 3c, respectively, and the RMSEs of target position, velocity, and acceleration tracking in Fig. 3d.

Table 2 Relevant motion parameters of trajectory 2

Time (s)	Acceleration (m/s^2)
0–60	0
60–200	10

The proposed tracking algorithm still has very good tracking performance for target trajectory 2. The estimates and the real values of the target trajectory still coincide well. The estimates of target speed fluctuate in the vicinity of the real values and the fluctuation frequency is a little high, but the fluctuation range is very small. The RMSEs of the target acceleration estimates are less than 2, and the maximum acceleration error just occurs at the acceleration

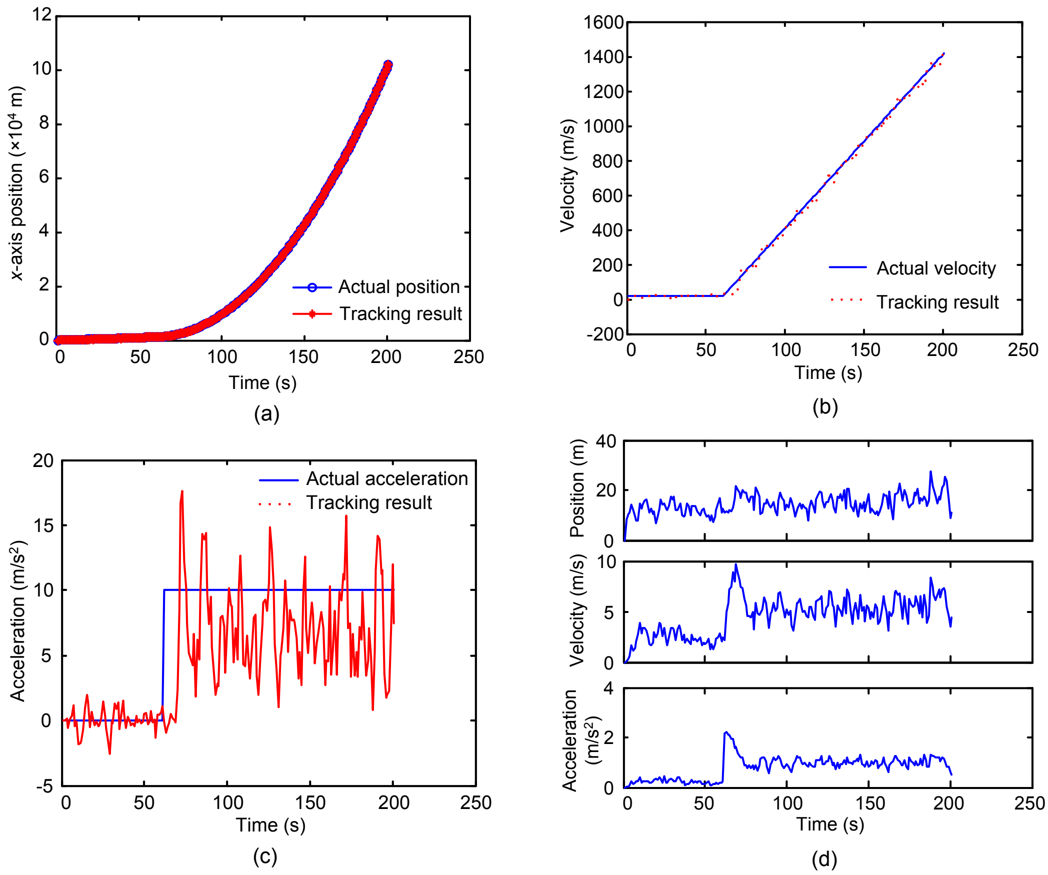

Fig. 3 Tracking results of the uniform motion - uniform acceleration motion target

(a) Target trajectory 2 and its tracking result; (b) Target velocity and its tracking result; (c) Target acceleration and its tracking result; (d) RMSE of target position, velocity, and acceleration tracking

transition time, namely at the 60th second. Since the acceleration estimates based on the proposed algorithm are continuous, the tracking results of acceleration are also in line with the real values. Overall, for the uniform motion - uniform acceleration target, the proposed algorithm meets the requirements of tracking performance.

4.3 Trajectory 3: serpentine locomotion

The target moves along a serpentine route. The initial state of the target is x_0={0 m, 50 m/s, 0 m/s^2}, the total running time is 200 s, and other relevant motion parameters are as shown in Table 3. The target motion trajectory is as shown in Fig. 4a.

For the serpentine locomotion target shown in Fig. 4a, the tracking results of the target motion trajectory, velocity, and acceleration in the x-direction are shown in Figs. 4a, 4b, and 4c, respectively, and the RMSEs in Fig. 4d.

Table 3 Relevant motion parameters of trajectory 3

Time (s)	Acceleration (m/s^2)
0–20	0
20–60	10
60–120	0
120–150	−20
150–200	0

Trajectory 3 is a type of motion with acceleration changing relatively frequently. Similar to trajectory 1 and trajectory 2, using the algorithm the target can be accurately tracked in terms of position and speed. Because the target acceleration changes relatively frequently and the acceleration is discontinuous, which are reflected by the RMSEs, when the acceleration changes, the errors are larger, and then the errors decrease gradually.

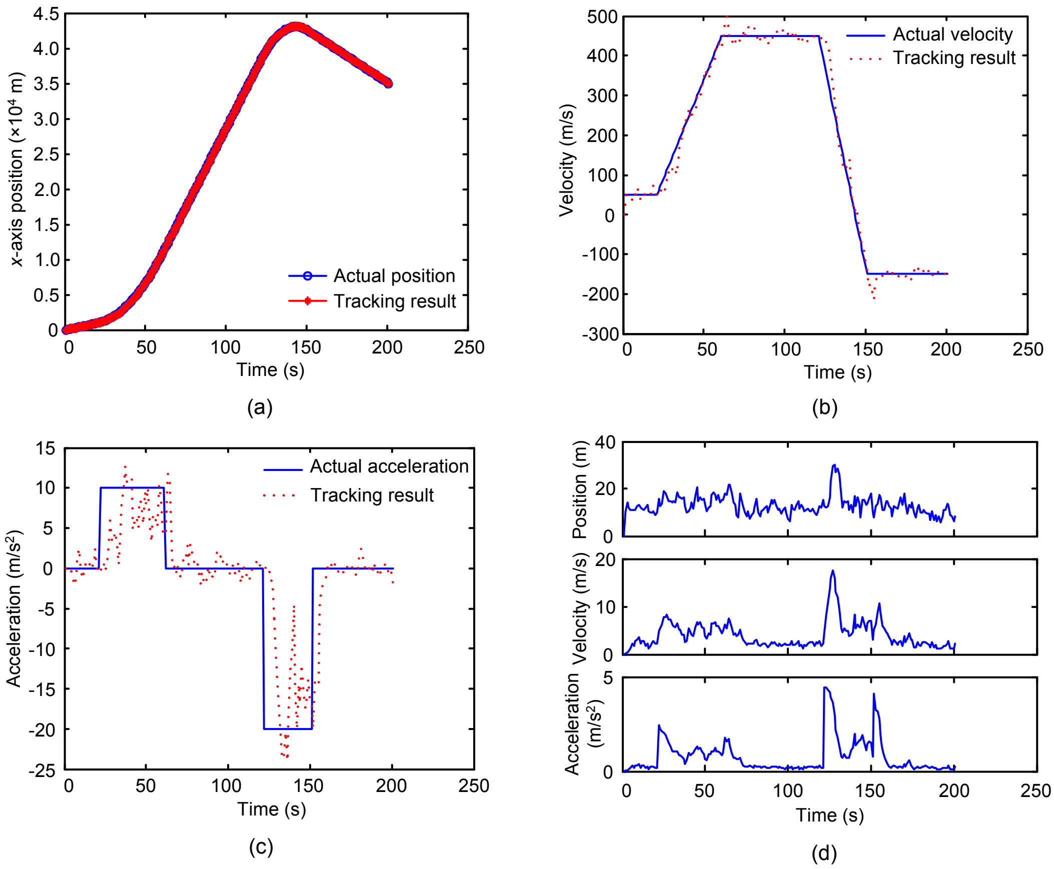

Fig. 4 Tracking results of the serpentine locomotion target

(a) Target trajectory 3 and its tracking result; (b) Target velocity and its tracking result; (c) Target acceleration and its tracking result; (d) RMSE of target position, velocity, and acceleration tracking

4.4 Trajectory 4: variable acceleration motion 1

The target takes a variable acceleration motion. The initial state of the target is x_0={0 m, 0 m/s, 20 m/s^2}, the total running time is 200 s, and other relevant motion parameters are as shown in Table 4. The target motion trajectory is as shown in Fig. 5a.

For the variable acceleration motion target shown in Fig. 5a, the tracking results of the target motion trajectory, velocity, and acceleration in the x-direction are shown in Figs. 5a, 5b, and 5c, respectively, and the RMSEs of the target position, velocity, and acceleration tracking in Fig. 5d.

Trajectory 4 is generated by a variable acceleration motion target. Similar to the previous three trajectories, using the algorithm the target can be accurately tracked in terms of position and speed. The larger target speed estimation errors occur just slightly behind the positions of acceleration mutation. Similar to trajectory 3, as the target acceleration changes relatively frequently and the accelerations are discontinuous, which are reflected by the RMSEs, when the acceleration changes, the target position, velocity, and acceleration tracking errors are larger, and then the errors decrease gradually.

Table 4 Relevant motion parameters of trajectory 4

Time (s)	Acceleration (m/s^2)
0–25	20
25–65	−20
65–105	20
105–145	−20
145–185	20
185–200	−20

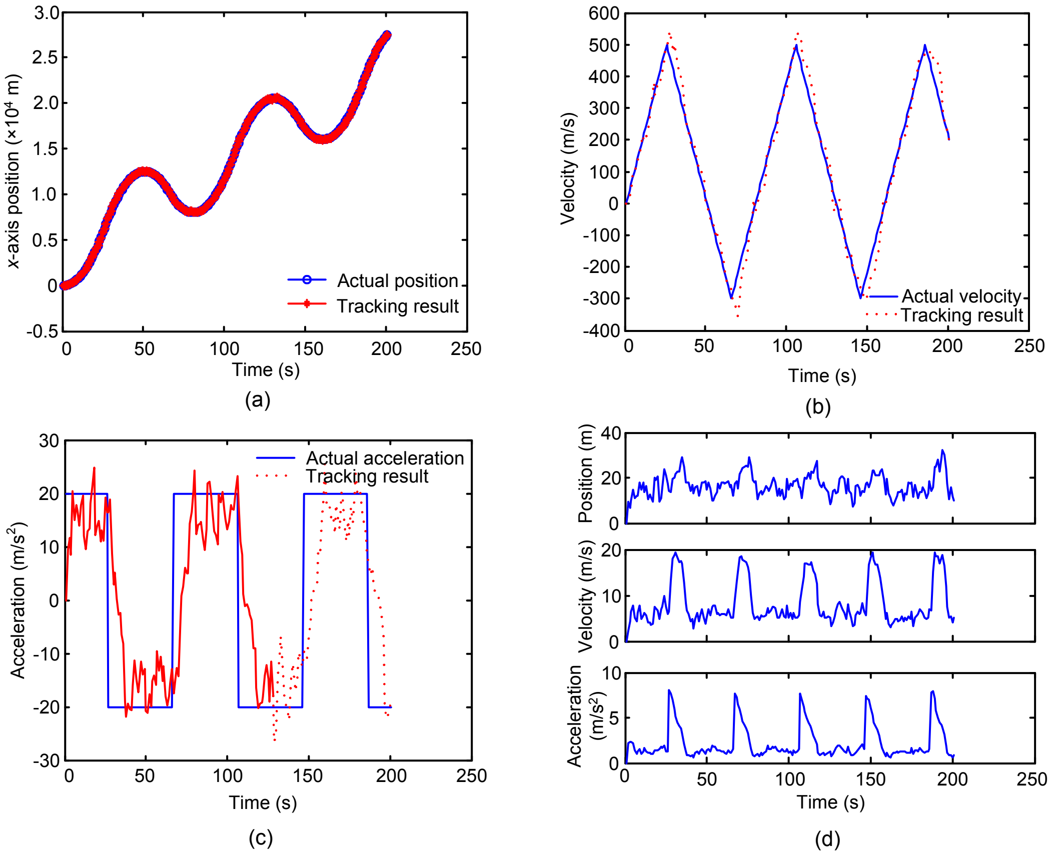

Fig. 5 Tracking results of variable acceleration motion target 1

(a) Target trajectory 4 and its tracking result; (b) Target velocity and its tracking result; (c) Target acceleration and its tracking result; (d) RMSE of target position, velocity, and acceleration tracking

4.5 Trajectory 5: variable acceleration motion 2

The target takes a variable acceleration motion. The initial state of the target is x_0={0 m, 0 m/s, −15 m/s^2}, the total running time is 200 s, and other relevant motion parameters are as shown in Table 5. The target motion trajectory is as shown in Fig. 6a.

For the variable acceleration motion target shown in Fig. 6a, the tracking results of the target motion trajectory, velocity, and acceleration in the x-axis direction are shown in Figs. 6a, 6b, and 6c, respectively, and the RMSEs of the target position, velocity, and acceleration tracking in Fig. 6d.

Trajectory 5 is also generated by a variable acceleration motion target. Similar to the previous four trajectories, using the algorithm the target can be accurately tracked in terms of position and speed. The larger target speed estimation errors also occur behind the positions of acceleration mutation. Similar to trajectories 3 and 4, as the target acceleration changes relatively frequently and the accelerations are discontinuous, which are reflected by the RMSEs, when the acceleration changes, the target position, velocity, and acceleration tracking errors are larger, and then the errors decrease gradually.

Table 5 Relevant motion parameters of trajectory 5

Time (s)	Acceleration (m/s^2)
0–25	−15
25–75	15
75–125	−30
125–175	30
175–200	0

Table 6 shows the position and velocity tracking errors of the fixed grid interacting multiple model (FGIMM) and adaptive grid interacting multiple model (AGIMM) algorithms for a certain serpentine locomotion target. When the target moves along a straight line, the position and velocity errors of the

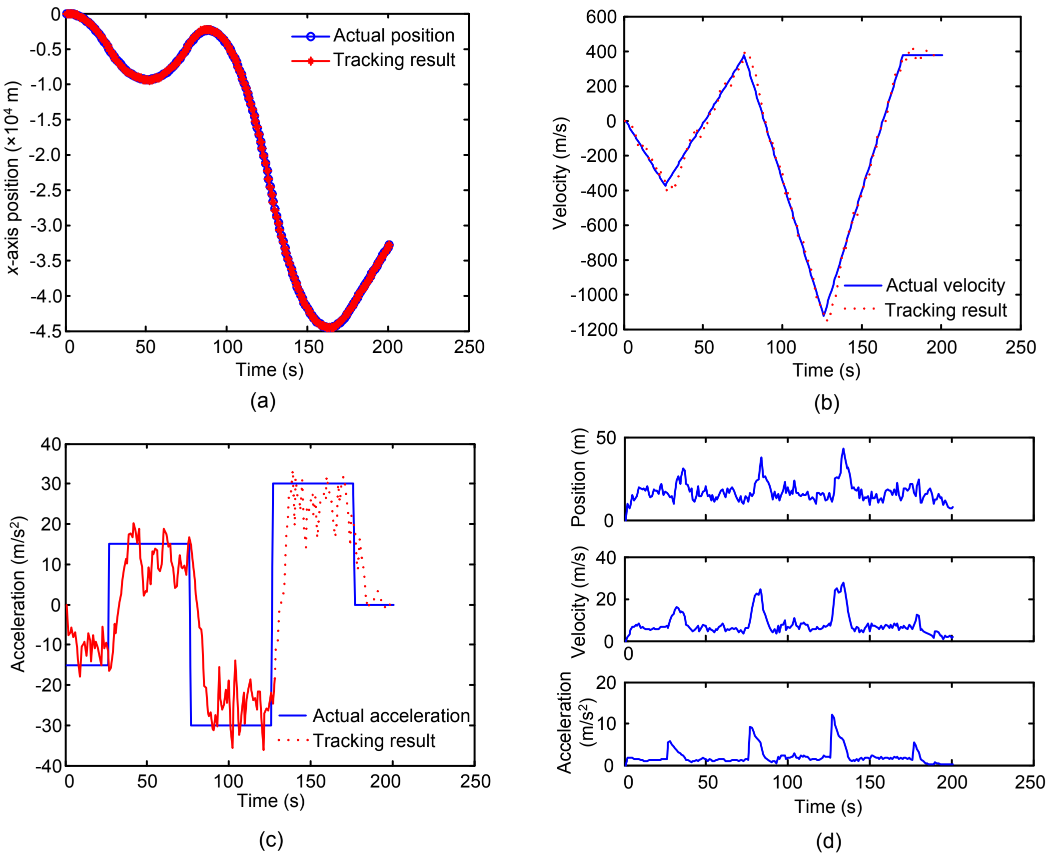

Fig. 6 Tracking results of variable acceleration motion target 2

(a) Target trajectory 5 and its tracking result; (b) Target velocity and its tracking result; (c) Target acceleration and its tracking result; (d) RMSE of target position, velocity, and acceleration tracking

Table 6 Performance comparison of FGIMM and AGIMM algorithms

Angular velocity (rad/s)	Position error peak (m)		Velocity error peak (m/s)	
	FGIMM	AGIMM	FGIMM	AGIMM
1.9	119	95	7.1	6.6
−3.2	71	56	6.5	5.6
5.0	96	84	23.9	4.0
−4.5	77	53	22.1	5.1

FGIMM: fixed grid interacting multiple model algorithm; AGIMM: adaptive grid interacting multiple model algorithm

two algorithms are almost the same. When the target takes weak maneuvering motions (ω=1.9, −3.2 rad/s), the differences of the position and velocity errors of the two algorithms are not significant. When the target takes strong maneuvering motions (ω=−4.5, 5.0 rad/s), the tracking accuracy of the FGIMM algorithm greatly decreases, and the position and speed tracking are in an unstable state and have obvious fluctuation; specifically, the velocity error is relatively large. Obviously, the AGIMM algorithm has better stability and adaptability than the FGIMM algorithm.

5 Conclusions

Aiming at the shipborne radar target tracking problem, a variable structure adaptive grid IMM tracking method is presented. Tracking experiments are performed using the proposed method for five typical maneuvering targets, namely a uniform motion - uniform acceleration motion target, a uniform acceleration - uniform motion target, a serpentine locomotion target, and two variable acceleration motion targets. Experimental results show that the proposed method can accurately track the maneuvering targets. The estimates of the target trajectory obtained are basically coincident with the real values of the target trajectory. Other than a short time after acceleration mutation, the tracking errors of target position, speed, and acceleration at other positions are very small. We can conclude that the proposed method has good tracking performance, including high tracking accuracy and good adaptability to various maneuvering targets.

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