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Adaptive Filtering Techniques in Radar Tracking System With Variable-Structured Multiple-Model Estimator

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ABSTRACT

In this paper, the variable-structured multiple-model (VSMM) estimator is utilized for tracking maneuvering aircraft radar (AR) targets. Two adaptive filtering techniques, i.e. adaptive grid (AG) and switching grid (SG) techniques, are developed and investigated. To evaluate and compare the performances of the presented algorithms with the respective fixed structure multiple-model (FSMM) algorithm and the interacting multiple model (IMM) method, several different test scenarios are studied by Monte-Carlo simulation. The comparative analysis has revealed better performance characteristics and substantial computation saving of two proposed approaches in comparison with the corresponding FSMM algorithm and IMM method.

Keywords: maneuvering target tracking, adaptive filtering, variable-structured, Kalman filter

用變結構多模估計器於雷達追蹤系統中之適應濾波技術

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摘 要

本文提出利用變結構多模演算法(VSMMA)來追蹤瞬變目標。文中兩種演算法架構,即適應式框格與交換式框格技術，分別被發展出來並進行分析。為了評估與比較此兩種方法之性能，我們分別列舉了兩個實例來與固定架構之多模演算法(FSMMA)，IMM 法進行比較。經由蒙地卡羅法模擬分析後，結果發現此一新的方法具有較佳之追蹤性能與較少之運算特性。

關鍵詞：瞬變目標追蹤，適應式濾波，變結構，卡爾曼濾波器

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I. INTRODUCTION

The standard Kalman filter can optimally estimate the target motion from noisy radar data, however it fails to perform satisfactory for maneuvering target tracking. If the target is maneuvering, a situation where the target is suddenly accelerated by the pilot, the tracking errors may develop and lead to eventual track loss using the conventional Kalman filtering. In order to detect and estimate the abrupt changes in parameter systems, a number of researchers have proposed techniques modifying conventional Kalman filtering for maneuvering target tracking. Approaches based on Kalman filter include the early work of Singer [1], who augments the Kalman filter with the target acceleration equation represented by a first-order autoregressive process. Berg [2] has improved Singer's model by adding a mean jerk term assuming that a target makes a coordinate turn. Zhou and Kumar [3] presented a "current model" concept in describing the statistical distribution of maneuvering acceleration. In this model, the acceleration in next time is limited in the neighborhood of current acceleration, and obeys a modified Rayleigh distribution. An adaptive state estimation algorithm based on a modified system model, which was a sequence of unknown pilot command vectors drawn from a finite set, for tracking a two-dimensional maneuvering target has been reported by Moose et al. [4] and extended to three-dimensional target using spherical observation (radar data) [5,6].

Since the exact statistics of maneuvering acceleration cannot possibly be known, it is necessary to develop an adaptive estimation method. The input estimation approach for tracking a maneuvering target is proposed by Chan, et al. [7]. In this approach, the magnitude of the acceleration is identified by the least-squares estimation when a maneuver is detected. A technique, described by McAulay and Denlinger [8], involves statistical decision theory and using two different filters to estimate maneuvering and non-maneuvering states, respectively. Thorp [9] also presented a method to detect target maneuvering and modeled maneuvering target motion by introducing a binary random variable in the target state equation. The variable-dimensional filtering technique is proposed by Bar-Shalom, et al. [10]. In this technique, when a maneuver is detected, the state model for the target is changed by introducing extra state components (the target acceleration). This filter is able to track a target in maneuvering mode as well as in non-maneuvering mode with reduced estimation error.

Multiple-model (MM) estimation [11], as a powerful technique to adaptive estimation, has received a great deal of attention in recent years due to its unique power to handle problems with structural and parametric uncertainties, and to decompose a complex problem into simple subproblems. However, this method cannot handle systems with mode jumps because its individual mode-based filters do not interact with each filter. The Interacting Multiple Model (IMM) technique, based on the Bayesian rule, has been proposed to treat this issue by Blom and Bar-Shalom [12]. The IMM filter consists of a second-order model for the quiescent mode of the target and one or two third-order models with different process noise levels for the maneuvering mode. The IMM filter is efficient in tracking maneuvering targets, but requires a priori the suitable choice of model transition probability and process noise covariance of the target maneuvering model according to the target maneuvering input level.

Most existing multiple-model estimators have a fixed structure (FS), including the IMM estimator, in the sense that they use a fixed set of models at all time. However, in the FSMM estimator increasing the number of submodels cannot guarantee better tracking performance due to the unnecessary competition among submodels which are not consistent at the current moment. To circumvent this situation one could think of combining the IMM approach with the moving-bank MM adaptive estimation approach [13]. This basic idea has been thoroughly studied in a general variable-structured MM estimation and laid down a theoretical foundation [14] for MM estimation without the limitation of the FS. Since the development and design of VSMM algorithms received increasing attention recently due to their great practical significance, it has become more and more clear that VS is probably the main practical approach to make MM estimators cost-effective enough for real-world applications with a large model set. So far, all the existing VSMM algorithms are more or less ad hoc and thus valid only for the problems considered in that no general techniques were proposed for.

The object of this study will be to further develop the VSMM estimator. From a computation standpoint, the less number of the subfilter is attractive for many tracking applications, e.g. high data-rate tracking systems. In order to minimize the errors produced from dynamic modeling in unusual conditions and computation complexity, two new maneuvering target tracking approaches are presented, which combine a MM algorithm with variable structure, a simple decision rule and the covariance matching technique. This paper makes two contributions. First, we derive two efficient modified algorithms for variable-structured state estimation in radar tracking system. An adaptive grid (AG) MM algorithm [13] and a switching grid (SG) MM algorithm [15] are cast as in the framework of VS. Second, we study and compare the capabilities of the presented AG and SG techniques in the application of maneuvering AR tracking. The grids used to describe the multiple models, as mentioned in [15], are set over the continuous interval of the target acceleration, within the framework of the target model. The adaptive grid algorithm determines the values of the grid points within a moving-bank of filters at each time step. Otherwise, the switching grid algorithm uses a switchable subset of a predetermined model sets within the same continuous acceleration interval. The computer simulation results show that the proposed algorithms based on these methods can achieve the better accuracy than FSMM algorithm (FSMMA) and IMM method with a lower computational complexity.

II. PROBLEM FORMULATION

The design of the MM tracking filters involves a selection of aircraft models and determination of their parameters. As a base for the MM spacing, let us assume that the only measurements in tracking radar system are range $\Re$ and bearing angle θ , and filtering is performed in the rectangular coordinates (two dimensional), so that the measurements must first be transformed. The transformation equations are

$$X(t)= \Re \cos\theta$$
$$Y(t)= \Re \sin\theta \quad (1)$$

The target state equation of motion can be modeled by

$$X(k+1) = \Phi X(k) + \Gamma[U(k) + W(\mathrm{k})] \quad (2)$$

where

$$X(k)=\begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \end{bmatrix} \text{ (the target state vector at time k)}$$

Here $x(k)$, $y(k)$ and $\dot{x}(k)$, $\dot{y}(k)$ represent the target positions and speeds in the x- and y-direction respectively.

$$\Phi = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \text{(the state transition matrix)}$$

$$\Gamma = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix} \text{ (the input matrix)}$$

where T is the sampling interval, and

$$U(k)=\begin{bmatrix} U_x(k) \\ U_y(k) \end{bmatrix} \text{ (the deterministic acceleration)}$$

$W(k) = \begin{bmatrix} W_x(k) \\ W_y(k) \end{bmatrix}$ (the input noise vector, which is assumed to be white zero mean with covariance Q)

where

$Q(k) = E\{W(k)W^T(k)\}$, $E\{W(k)W^T(k+j)\}=0$, $\forall j \neq 0$.

The initial state estimate is $\hat{X}(0/0)$ with initial covariance $P(0/0)$.

The measurement equation is

$$Z(k) = H\ X(k) + V(k) \quad (3)$$

where

$Z(k) = \begin{bmatrix} Z_x(k) \\ Z_y(k) \end{bmatrix}$ (the observation vector at time k),

$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$ (the measurement matrix).

$V(k) = \begin{bmatrix} V_x(k) \\ V_y(k) \end{bmatrix}$ (the vector of zero mean Gaussian measurement noise with covariance R),

where
$R(k)=E\{V(k)V^T(k)\}, E\{V(k)V^T(k+j)\}=0, \forall j\neq 0$.

The difficulty in tracking a maneuvering target is caused by the uncertainty in the suitability of the target model being used. Therefore, there is a need to have several possible models available in MM algorithm and to have a scheme which switches to the most appropriate model, or weights the estimates according to model probability from all the individual models. However, for the FSMMA increasing the number of models increases considerably the computation load, but does not guarantee better tracking performance. In fact, the performance will deteriorate if too many models are used due to excessive competition from the unnecessary models. The variable-structured approach may treat this dilemma with fewer subfilters in the tracking algorithm that can provide the same or better performance than the fixed-structure filters. This provides the motivation for exploring new approaches to make the MM algorithm more flexible and practical. In the following text two schemes of VSMM tracking estimator will be developed and implemented.

III. VARIABLE-STRUCTURED MULTIPLE MODEL (VSMM) ESTIMATOR

In the multiple model estimation, it is assumed that the possible system behavior structures can be represented by a set of models. Meanwhile, a bank of filters runs in parallel at every time, each bases on a particular model, to obtain the model-conditioned estimates. The overall state estimate can then be obtained by a certain combination of these model-conditioned estimates. It is known that a pilot command has a finite continuous range of acceleration that can be selected and this is assumed to be quantized to a discrete number n of possible accelerations $U_i=\{U_{ix},U_{iy}\}$, where i=1,2,…,n. Each of the acceleration corresponds to a model, which probability can be calculated by a recursive technique for estimating $U(k)$. The sequence of the pilot command U_i is unknown to the tracking system that can be modeled as a Markov process. When these are made, the bank of filter will be augmented by a recursive technique for estimating $U(k)$. Thus the optimal estimate $\hat{X}(k+1)$ of $\hat{X}_i(k+1)$, based on the measurement sequence $\bar{Z}(k+1)=\{Z(1),...Z(k+1)\}$, is described by

$$\hat{X}(k+1)=\sum_{i=1}^{n}\hat{X}_i(k+1)\mu[U(k+1)=U_i(k)/\bar{Z}(k+1)] \quad (4)$$

where $\mu[.]$ is the probability that the target is in state i at time k+1.

MM estimation has been successfully applied to a number of practical problems and has exhibited promising results in the tracking of maneuvering targets. However, one basic problem with this approach is the number of filters in the bank. For instance, if there are two uncertain parameters (such as U_{ix}, U_{iy} in the x- and y-direction, respectively) and each can assume ten possible values, then 100 separate filters must be implemented. This situation may possibly lead to a predicament in computation and an unfeasibility for application. To circumvent this problem, one can think of implementing a moving bank of fewer filters to slide among all possible models. Meanwhile, this moving bank can be steered by a decision rule, which can decide when to move the bank and in what direction. It is also able to change the size of the bank at any time by altering the discretization level in parameter space.

Although maintaining fewer elemental filters in the bank can enhance the feasibility of the MM algorithm, it could aggravate the behavior of making hasty decisions when the true model is not included in the filter's model set. Thus some additional means are needed for the algorithm to remedy this drawback. Generally, it is essential to find a good strategy for completing the conflicting tasks of simultaneously minimizing the number of filters and the chance of hasty decision in the algorithm.

3.1 The VSMM scheme

In the following two practical VSMM schemes, i.e. adaptive grid and switching grid schemes, are proposed and outlined.

3.1.1 *Switching grid (SG) scheme*

First, in the SG scheme, the decision rule consists of the following two major elements: 1) design of model-set cover, and 2) design of candidate model-set activation logic and selection of the thresholds for the termination of model sets. For i = -n+1,…, 0,…, n-1, it is chosen D^i to be the digraph containing the model subset $U^i = \{U_{i-1}, U_i, U_{i+1}\}$ as the vertices set, and a transition between models in a subset is governed by a Markov chain, named as the transition probability θ_{ij}, which is selected at the beginning of the algorithm. The large set of models based on different U_i can be divided into subsets as shown in Figure 1, where each subset contains only three models.

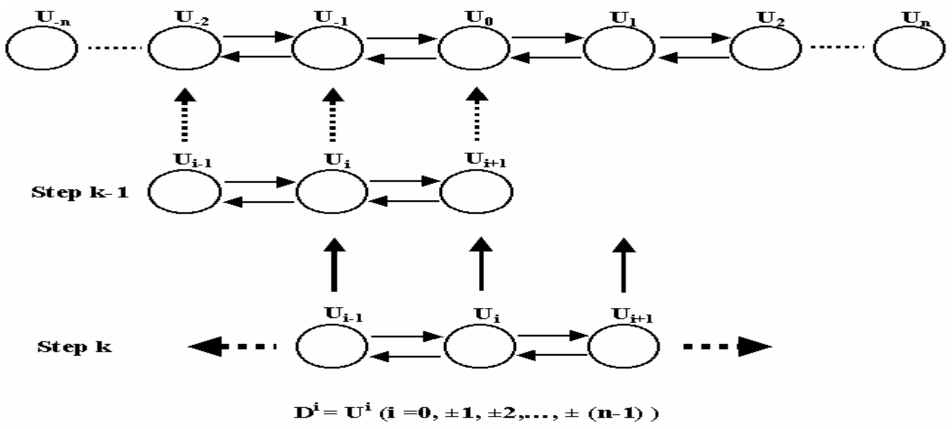

Fig. 1. The supporting digraph D of the switching grid (SG) scheme.

he real value of the maneuvering target current acceleration U_i is assumed to be within the continuous range $[-U_{max}, U_{max}]$, where U_{max} is the maximum acceleration of target with physical limitations. It is chosen D_k to be the time-varying supporting digraph at time k, and model set U_k^i = $[U_{i-1}(k), U_i(k), U_{i+1}(k)]$ for grid values (vertices of D_k) $U_{i-1}(k), U_i(k), U_{i+1}(k) \in [-U_{max}, U_{max}]$, $i = -n+1, \ldots, 0, \ldots, n+1$. Initially, suppose the SGMM algorithm is started with the $D_{k-1} = D^i$ for some i = -n+1, …, n-1. The recursive subdigraph switching logic is set up according to the following adaptation rule.

$$D_k = \begin{cases} D^{i-1}, & if \quad \mu_{i-1}(k-1) > \gamma_p \\ D^i, & if \quad \mu_i(k-1) > \gamma_p \\ D^{i+1}, & otherwise \end{cases} \qquad (5)$$

where $\gamma_p > 0.5$ is a threshold for selecting the significant model. $\mu_{i-1}(k), \mu_i(k), \mu_{i+1}(k)$ are the SGMM model's posterior probabilities, which can be obtained from the Eq.(26).

The switching logic is the kernel of the SGMM algorithm and contains the following two functions: 1) At the beginning, the decision assigns an arbitrary model subset to the adaptation rule. 2) At each time step it checks the posterior probability for each model, and makes a decision as to whether a subset shift is necessary or not. If a subset shift is indicated then a new movement is executed; if no subset shift then the old one is maintained.

3.1.2 *Adaptive grid (AG) scheme*

The current acceleration U_i is assumed to be within the continuous range $[-U_{max}, U_{max}]$, which is the same as the preceding section 1. The model set M_k = $[U_L(k), U_C(k), U_R(k)]$ for grid values (vertices of D_k) $U_L(k), U_C(k), U_R(k) \in [-U_{max}, U_{max}]$, $k = 1, 2, \cdots$. L, C, R stand for left, center, right model of the MM configuration, respectively. The large set of models based on different U_i, i =1,2,…, n can be divided into subsets as shown in Figure 2, where

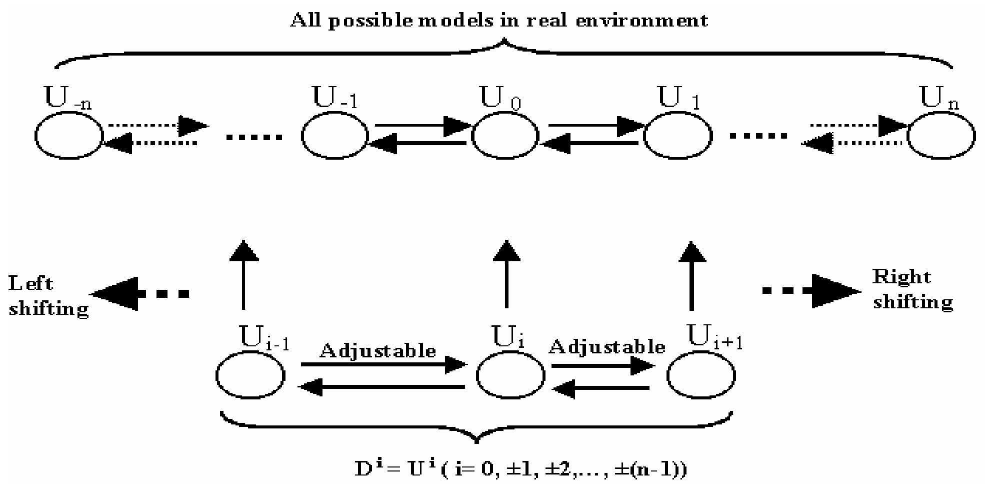

Fig. 2. The supporting digraph D of the adaptive grid (AG) scheme.

each subset represents a possible moving bank in one-dimensional space at any time and contains only three models, viz., right, center and left model. An arrow from one model to another indicates a legitimate model switch and self-loops are omitted (i.e., each model may stay in itself for some time). Both size and center of the bank could be adjusted according to the following decision rule.

Initially the AGMM algorithm (AGMMA) is started with the coarse grid $D_0 = \{U_L(0) = -U_{\max}, U_C(0) = U_0, U_R(0) = U_{\max}\}$ As each time step proceeds (k→k+1), the grid is adjusted according to the following two adaptation logic steps.

3.1.2.1 *Grid center readjustment*

$$U_c(k+1)=\begin{cases}\mu_L(k)U_L(k)+\mu_C(k)U_C(k)+\mu_R(k)U_R(k), & if\ \ \mu_C(k)\le\gamma_1\\ U_C(k), & otherwis\end{cases} \tag{6}$$

where $\mu_L(k), \mu_C(k), \mu_R(k)$ are the AGMM mode's posterior probabilities. $\gamma_1 < 0.1$ is a threshold for detecting a jump action of the center.

In this adjustment, the moving bank seeks to center itself on the current estimate of the parameter $U_c(k+1)$. This action can make the bank more flexible to adapt to the variation of the true parameter. When the probability of the center model becomes less than a selected threshold γ_1, the bank center would jump to a new position at time k+1. Otherwise, the bank stays at its original position.

3.1.2.2 *Grid distance readjustment*

Case (1) No jump (Significant center mode)
$\mu_C(k) = Max\ \{\mu_L(k), \mu_C(k), \mu_R(k)\}$

$$U_L(k+1)=\begin{cases}U_C(k+1)-\delta_L(k)/2, & if\ \ \mu_L(k)<\gamma_1\\ U_C(k+1)-\delta_L(k), & otherwise\end{cases} \tag{7}$$

$$U_R(k+1)=\begin{cases}U_C(k+1)+\delta_R(k)/2, & if\ \ \mu_R(k)<\gamma_1\\ U_C(k+1)+\delta_R(k), & otherwise\end{cases} \tag{8}$$

where $\delta_L(k) = Max\ \{U_C(k) - U_L(k), d_a\}$, $\delta_R(k) = Max\ \{U_R(k) - U_C(k), d_a\}$, $\gamma_1 < 0.1$ is a threshold for detecting an unlikely mode, and d_a is a model separation distance.

When the center model of the bank has the maximum probability of all models, the moving bank maintains at its original state. Meanwhile, if either the left model or right model were detected to be an unlikely model (e.g. μ_L or μ_R is less than a selected threshold γ_1), the corresponding model separation distance (δ_L or δ_R) would be reduced by half. This reduced action can contract the size of the bank and decrease the steady-state estimation errors.

Case (2) Left jump (Significant left mode)
$\mu_L(k) = Max\ \{\mu_L(k), \mu_C(k), \mu_R(k)\}$

$$U_L(k+1)=\begin{cases}U_C(k+1)-2\delta_L(k), & if\ \ \mu_L(k)>\gamma_2\\ U_C(k+1)-\delta_L(k), & otherwise\end{cases} \tag{9}$$

$$U_R(k+1) = U_C(k+1) + \delta_R(k) \tag{10}$$

where $\gamma_2 > 0.9$ is a threshold for detecting the significant mode.

When the left model of the bank has the maximum probability of all models, an expansion of the bank in the left side is indicated. Meanwhile, the corresponding model separation distance between the bank center and left model would be increased by a factor of two.

Case (3) Right jump (Significant right mode)

$$\mu_R(k) = Max\{\mu_L(k), \mu_C(k), \mu_R(k)\}$$

$$U_L(k+1) = U_C(k+1) - \delta_L(k) \quad (11)$$

$$U_R(k+1) = \begin{cases} U_C(k+1) + 2\delta_R(k), & if \quad \mu_R(k) > \gamma_2 \\ U_C(k+1) + \delta_R(k), & otherwise \end{cases} \quad (12)$$

Similarly, when the right model of the bank has the maximum probability of all models, the bank size in the right side would be expanded by a factor of two.

Two different VSMM schemes have been defined as above. In the SGMMA, it keeps only these subfilters of the FSMM that are likely at the current time and excludes the redundant subfilters. It is potentially capable of achieving better tracking accuracy than the FSMMA. On the other hand, the AGMMA centers the grid center around the current value of the acceleration and adapts the grid distances depending on the jumping conditions of the filter. It is advantageous that the moving grid points in the AGMMA are not predetermined and they can have arbitrary values within the continuous maneuvering interval.

3.2 Compensating

Usually, we assume that the target has a smaller number of possible accelerations for saving the computation time in a real environment. However, this will mean that the actual plant input is not a member of the given model set, but is somewhere in between. Thus there is a need of an additional error covariance term to compensate for this system uncertainty.

The basic idea of compensating this system uncertainty is to adopt the covariance-matching technique to make the practical residuals consistent with their theoretical covariance. Let e(k+1) be the estimation error, it can be written as

$$e(k+1) = Z(k+1) - H\hat{X}(k+1) \quad (13)$$

Thus the actual covariance $e_p(k+1)$ of $e(k+1)$ is approximated by its sample covariance.

$$e_p = E\{e(k+1)e(k+1)^T\}$$

$$= \left[Z(k+1) - H\hat{X}(k+1)\right]\left[Z(k+1) - H\hat{X}(k+1)\right]^T \quad (14)$$

Otherwise, the theoretical covariance can be written as

$$e_{th} = HAP(k)A^T H^T + HBQB^T H^T + R \quad (15)$$

Then

$$HBQB^T H^T = e_p - HAP(k)A^T H^T - R \quad (16)$$

where $Q(k)$ can be obtained by

$$Q(k) = \begin{cases} GE_n, & if \quad E_n > 0 \\ 0, & otherwise \end{cases} \quad k=0,1,2,\ldots(17)$$

where $E_n = e_p - HAP(k)A^T H^T - R$, and G is a weighting matrix.

The input noise W(k) is assumed to be independent of each direction such that

$$Q(k) = \begin{bmatrix} q_x(k) & 0 \\ 0 & q_y(k) \end{bmatrix} \quad (18)$$

In order to avoid the large variation of $Q(k)$ in a normal process, the average of $Q(k)$ is taken in deriving an adaptive condition with respect to the target model. The compensation algorithm is

$$Q(k+\ell) = \ell^{-1}\sum_{h=1}^{\ell} Q(k+h) \qquad (19)$$

3.3 Weighting and estimate combination

The modified Kalman filter, which includes a deterministic acceleration in the motion model being used and an adjustable covariance Q(k) as described in section B. The filter equations are:

$$\hat{X}_i(k+1) = \overline{X}_i(k+1) + Kv_i(k+1) \qquad (20)$$
$$\overline{X}_i(k+1) = \Phi\hat{X}_i(k) + \Gamma U_i(k) \qquad (21)$$
$$v_i(k+1) = Z(k+1) - H\overline{X}_i(k+1) \qquad (22)$$
$$K(k+1) = M(k+1)H^T[HM(k+1)H^t + R]^{-1} \qquad (23)$$
$$M(k+1) = \Phi P(k)\Phi^T + \Gamma Q(k)\Gamma^T \qquad (24)$$
$$P(k+1) = [I - K(k+1)H]M(k+1) \qquad (25)$$

By using Bayes' theorem and $\overline{Z}(k+1) = \left\{\overline{Z}(k), Z(k+1)\right\}$, the mode's posterior probability may be obtained by

$$\mu[U(k+1)=U_i/\overline{Z}(k+1)] = C\cdot\mu[Z(k+1)/U(k+1)=U_i,\overline{Z}(k)]\sum_{j=1}^{n}\mu[U(k)=U_j/Z(k)]\cdot\Theta_{ij} \qquad (26)$$

where $\Theta_{ij} = \mu[U(k+1)=U_i/U(k)=U_j]$ and C is a constant obtained by $\mu[\overline{Z}(k+1)/\overline{Z}(k)]$.

Besides, it is pointed out that $\mu[Z(k+1)/U(k+1)=U_i,\overline{Z}(k)]$ is approximately normally distributed when the probability of a transition occurring between samples is small and will be represented by the Gaussian density function N {(mean), (variance)} established from the Kalman filtering algorithm conditioned on U_i. That is

$$\mu[Z(k+1)/U(k+1)=U_i,\overline{Z}(k)] \cong \mathrm{N}\left\{(H\Phi\hat{X}_i(k) + H\Gamma U_i(K)),(HM(k+1)H^T + R)\right\} \qquad (27)$$

The probability $\mu[U(k+1)=U_i/U(k)=U_j]$ is approximately by 0.95 for $i=j$ and 0.05/(n-1) for $i\neq j$. $\mu[U(k)=U_j/\overline{Z}(k)]$ is known from a previous recursive calculation.

The final estimate at scan k+1 is generated by combining the estimate from all the filters, that is

$$\hat{X}(k+1) = \sum_{i=1}^{n}\hat{X}_i(k+1)\cdot\mu[U(k+1)=U_i(k)/\overline{Z}(k+1)] \qquad (28)$$

and

$$\hat{U}(k+1) = \sum_{i=1}^{n}U_i\cdot\mu[U(k+1)=U_i/\overline{Z}(k+1)] \qquad (29)$$

The overall block diagram of the VSMM algorithm is shown in Fig. 3. In the block diagram, the main difference between the SG and AG scheme is that the block structure of decision rule has its own adaptation logic respectively, which has been derived in the section 1 and 2.

IV. SIMULATION RESULTS

In this section, the simulation results are evaluated on the basis of relative flops ratio (RFR), root mean square (RMS) error and the peak average error (PAE), which compares the performance of the proposed approaches with the FSMMA and IMM method. The IMM algorithm is outlined for N (=3) models in the following 5 steps, i.e. 1) Mixing of state estimates, 2) Model-conditioned updates, 3) Model likelihood computations, 4) Model probabilities update, and 5) Combination of state estimates. A derivation and detailed explanation of the IMM algorithm are given in [12]. The 'flops' is a function of MATLAB software, which returns the cumulative number of floating point operations. The PAE error is the measure of performance examined during target maneuvering period. The RMS error of state estimation and PAE are defined by

RMS estimation error at time k = $\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left\|X(k)-\hat{X}(k)\right\|^2}$, where N is the number of Monte Carlo simulation to run.

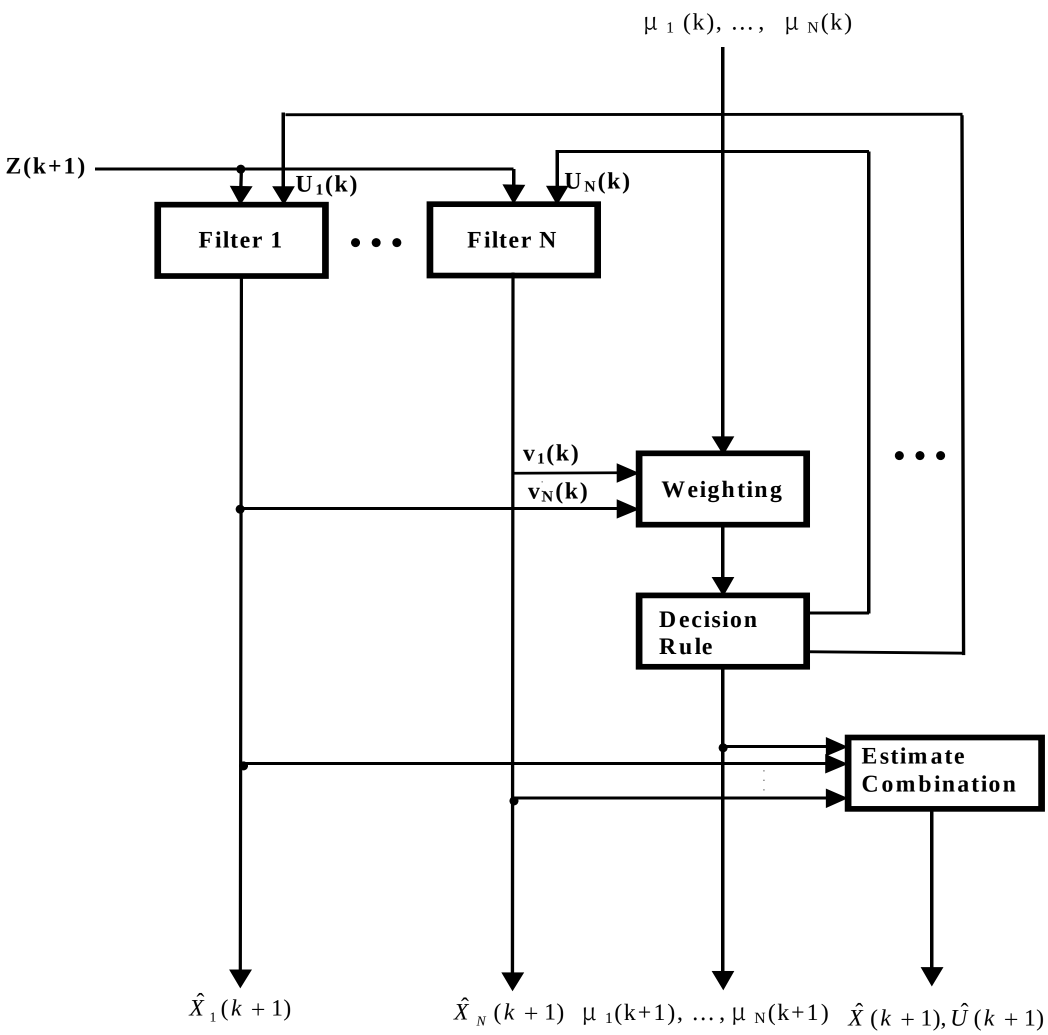

Fig. 3. The basic block diagram of the VSMM algorithm.

Peak average error (PAE) = $\frac{1}{\tilde{M}_p}\sum_{k=1}^{\tilde{M}_p}$(RMS estimation error at k) , where $\tilde{M}_p$ is the maneuvering period.

The state vector is represented in two-dimensional Cartesian coordinates, consisting of the position, speed and acceleration of the target. The parameters for the tracking algorithms are given by the following. U_{max} =150 m/s^2, G= $\begin{bmatrix} 0.25 & 0 \\ 0 & 0.25 \end{bmatrix}$, T=1 second, $\sigma_x = \sigma_y$ =100 m, γ_1=0.05, γ_2=0.95, γ_p= 0.6 and $d_a = 25$ m/sec^2. The submodel switching probability Θ_{ij} is a constant matrix with a large value on the diagonal elements and was selected the same for all the configurations as

$$\Theta_{ij} = \begin{cases} 0.95, & if\ i = j \\ \frac{0.05}{n-1}, & otherwise \end{cases}$$

(30)

The initial target position is at (1000 m, 2000 m) in the x-y plane with the initial speed 600 m/s along the x-axis. For each simulation a Monte Carlo simulation of 500 runs were undertaken using different random number seeds for the measurement noise of the target. Two different motion scenarios are considered and these are detailed in the following examples.

Example 1:

Consider a test trajectory of a maneuvering target with four fast turns as shown in Fig.4. The target maintains a constant course and speed until t= 100 s, that it takes a fast 90° turn with acceleration inputs a_x = − 60 m/s^2, a_y = 60 m/s^2. The second turn starts at t=110 s with a_x = − 60 m/s^2, a_y = − 60 m/s^2. After that, the third turn starts at t=120 s with a_x = 60 m/s^2, a_y = − 60 m/s^2. The fourth turn starts at t=130 s with a_x = 60 m/s^2, a_y = 60 m/s^2 and finishes at t = 140 s. For this example, the maximum acceleration was determined by the target dynamic limitation and set to be 15 g (150 m/s^2). Three possible accelerations (− 150 m/s^2, 0 m/s^2, 150 m/s^2) in each direction are respectively applied to all the tracking algorithms. In the following figures, the symbols "AG" and "SG" represent the proposed VSMM algorithms with AG and SG scheme respectively. Similarly, the symbols “FSMM” and "IMM" mean the fixed structure multiple-model algorithm and IMM algorithm. Fig.5 shows the RMS position errors of the proposed VSMM algorithms, FSMMA and IMM. In the figure it demonstrates that the estimation errors of four methods during the non-maneuvering period are smaller than the measurement noise. However, when the target makes a turn, the SGMM and AGMM algorithms provide the better performance in comparison with the other methods. The presence of the maneuver quickly produces large tracking errors of

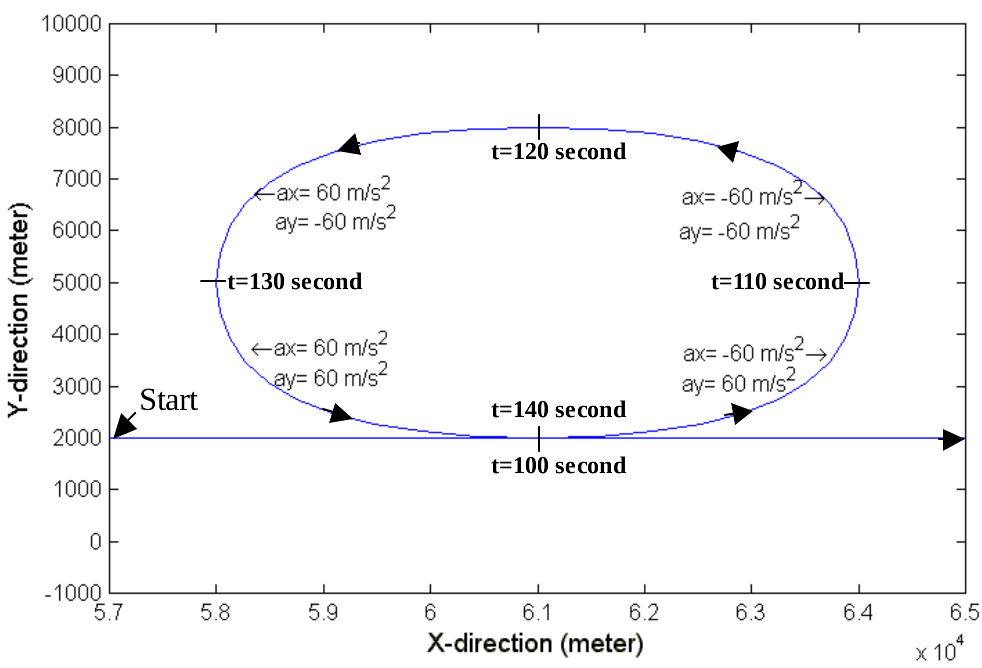

Fig. 4. A test trajectory of 6g maneuvering target with circular turn, Example 1.

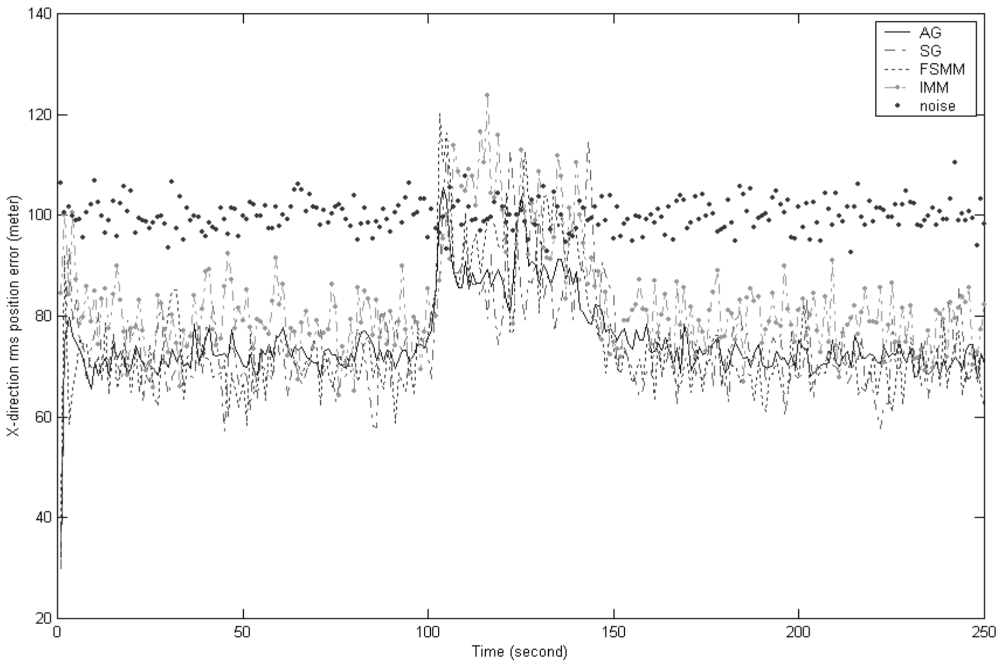

Fig.5. The RMS errors in position with $\sigma_x = \sigma_y$ =100 m, 500 Monte Carlo runs, Example 1.

position that are successfully corrected by the presented algorithms. Fig.6 and 7 show the plot of the target velocity and acceleration RMS errors for four methods. It is seen that during maneuvering phases SGMM and AGMM algorithms provide considerably better accuracy than FSMM and IMM. Meanwhile, the SGMM significantly outperforms the AGMM apart from the transient portions of the maneuver. The above figures reveal that the new algorithms with AG and SG scheme lower the velocity and acceleration bias in the maneuvering case and improve the tracking accuracy. Table 1 lists the computational complexity in terms of relative flops ratio, the quality of maneuver status reports, in terms of peak average errors (PAE) and RMS position and velocity errors of all methods with two different test scenarios. From the table (example 1) it is seen that during the maneuvering phases AGMM algorithm reduces the position PAE of the FSMM with about 8%, and the velocity with about 13%. Meanwhile, it reduces the position PAE of the IMM with about 10 % and the velocity with about 23%. Similarly, SGMM algorithm reduces the position PAE of the FSMM with about 12%, and the velocity with about 25%. Also, it reduces the position PAE of the IMM with about 14 % and the velocity with about 37%.

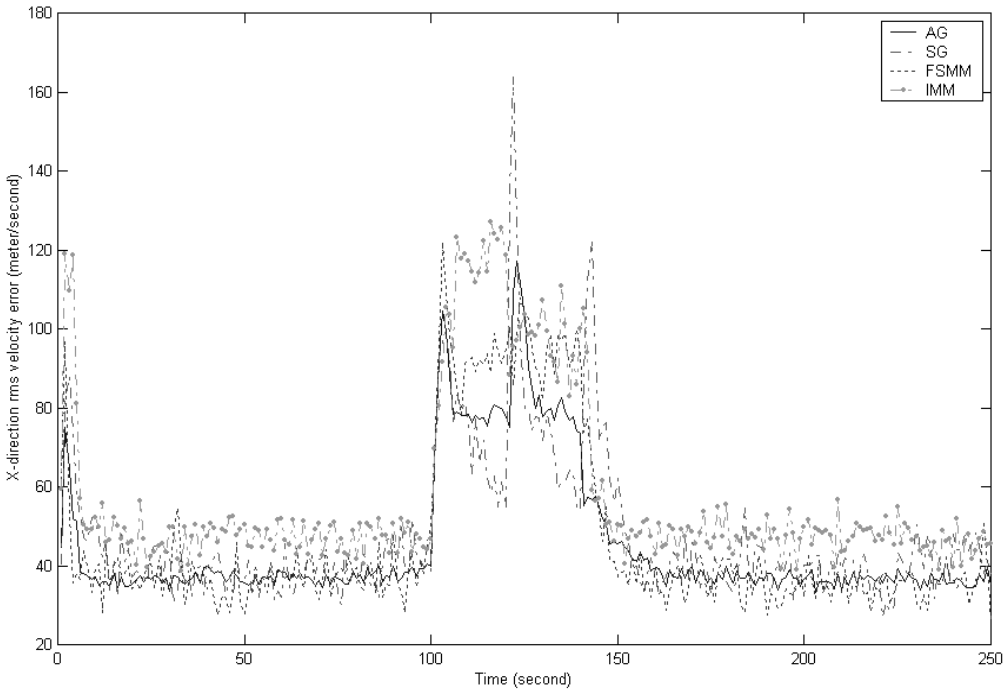

Fig.6. The RMS errors in velocity with σ_x σ_y =100 m, 500 Monte Carlo runs, Example 1.

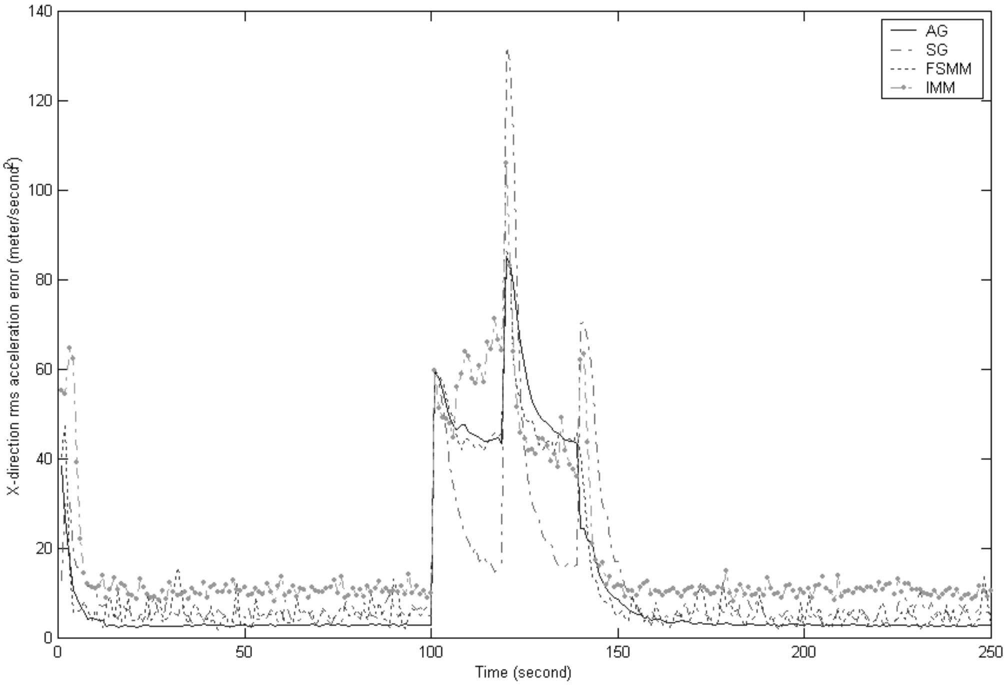

Fig.7. The RMS errors in acceleration with $\sigma_x = \sigma_y$ =100 m, 500 Monte Carlo runs, Example 1.

Table 1. RFR, PDE and RMS errors of position, velocity and acceleration estimation in two examples.

Example	CASE	Relative flops ratio(RFR)	RMS position error(m) (PAE)	RMS velocity error(m/sec) (PAE)	RMS acceleration error(m^2/sec) (PAE)
1	AG	1	75.19 (89.71)	45.54 (83.36)	11.61 (51.12)
	SG	0.97	74.90 (88.15)	47.64 (75.06)	12.46 (36.93)
	FSMM	1.41	74.85 (97.25)	47.42 (93.87)	13.69 (49.52)
	IMM	3.40	82.47 (98.22)	57.58 (102.91)	18.78 (53.44)
2	AG	1	74.22 (82.03)	43.27 (62.37)	7.98 (27.92)
	SG	0.97	73.93 (85.02)	45.82 (67.46)	11.10 (28.82)
	FSMM	1.41	72.60 (85.71)	43.29 (67.45)	11.16 (30.31)
	IMM	3.40	79.55 (81.52)	52.01 (63.64)	15.33 (28.68)

Example 2:

To further compare the tracking performance of the presented algorithms, another target motion scenario was created, in which the target performs a constant speed motion until t=100 sec, then it takes a slow 90° turn with $a_x = -20\ m/s^2$, $a_y = 20\ m/s^2$. The second turn starts at t= 130 s, after which it commences a fast 90° turn with $a_x = 120\ m/s^2$, $a_y = -120\ m/s^2$ and finishes at t=135 second. The test trajectory of a highly maneuvering target with slow-fast turn is shown in Fig. 8. Similarly, three possible accelerations in each direction are respectively applied to the proposed algorithms, FSMMA and IMM method. The RMS position errors of four methods are shown in Fig.9. When the maneuver level changes abruptly as shown in the figure, the algorithms based on the variable-structured scheme perform better than FSMMA and IMM method throughout the motion. Fig.10 depicts the velocity errors of four methods together. In the figure, during the interval that the maneuver level keeps 120 m/s^2, the tracking filter using FSMMA produces larger bias in speed, demonstrating that the FSMMA is inadequate to high-sustained maneuvering target. Meanwhile, we can see that the filter using the proposed SGMM (or AGMM) scheme has on average improved the performance and the smaller estimation errors in the same situation. Moreover, by comparing the tracking accuracy between IMM method

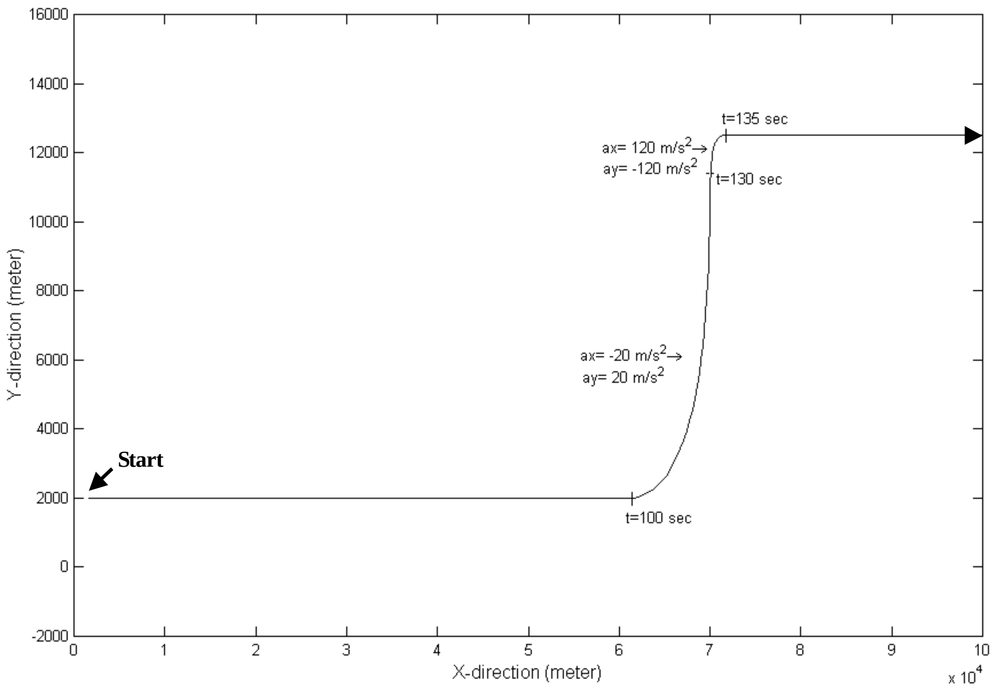

Fig. 8. A test trajectory of 12g maneuvering target with slow-fast turn, Example 2.

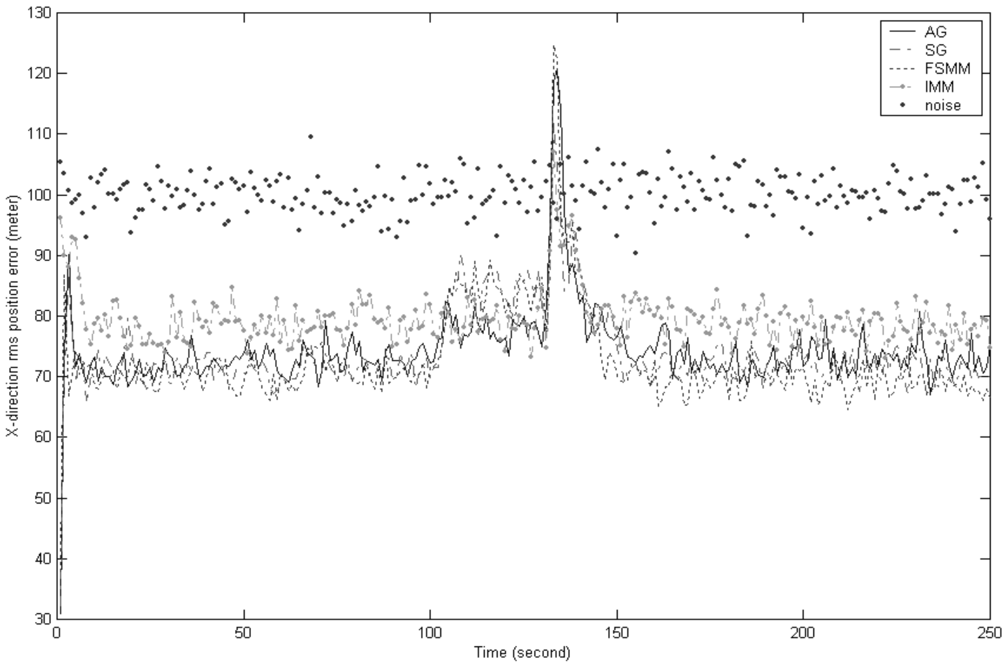

Fig. 9. The RMS errors in position with $\sigma_x = \sigma_y$ =100 m, 500 Monte Carlo runs, Example 2.

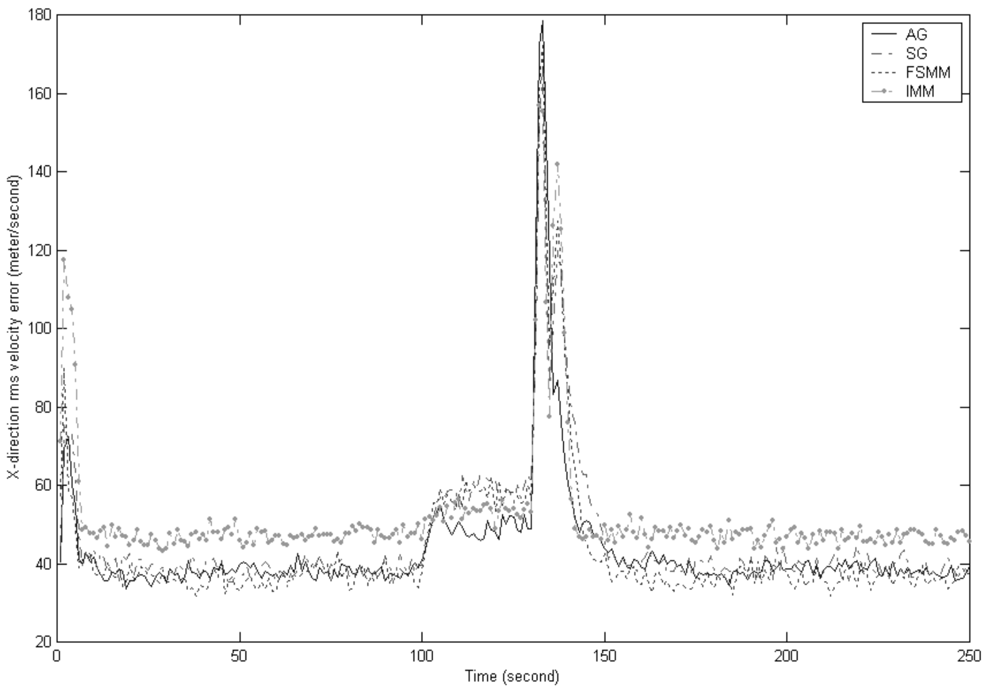

Fig. 10. The RMS errors in velocity with $\sigma_x = \sigma_y$ =100 m, 500 Monte Carlo runs, Example 2.

and presented algorithms, it is clear that the presented algorithms are better than the IMM method on the accuracy during the target moves with constant speed. Fig. 11 shows the acceleration error, as expected, we can see from the figure that the performance of the proposed methods have greatly smaller peak errors than FSMMA and IMM, and these errors decrease so fast that they do not accumulate and affect the succeeding estimates during the target maneuvers. From above figures, we can find that the tracking accuracy of the VSMM algorithms is superior to that of the FSMMA and IMM method, even though the computation complexity of our tracking algorithms is much lower than that of the FSMMA and IMM. Also, it is noted that the AGMM filter performs better than the SGMM in this example, at the expense of negligible computation load increasing. Moreover, the computation complexity, in terms of relative flops ratio (RFR), for the four algorithms is in the proportion 1 : 0.97 : 1.41 : 3.40 as to AGMMA : SGMMA : FSMMA : IMMA. It is worthwhile to note that increasing the number of models increases the RFR of FSMMA and IMMA, but does not increase the RFR of AGMMA and SGMMA, i.e., they have almost fixed computation load. If the total model-set is large in real-life problems, then this computational reduction can be expected to be more substantial.

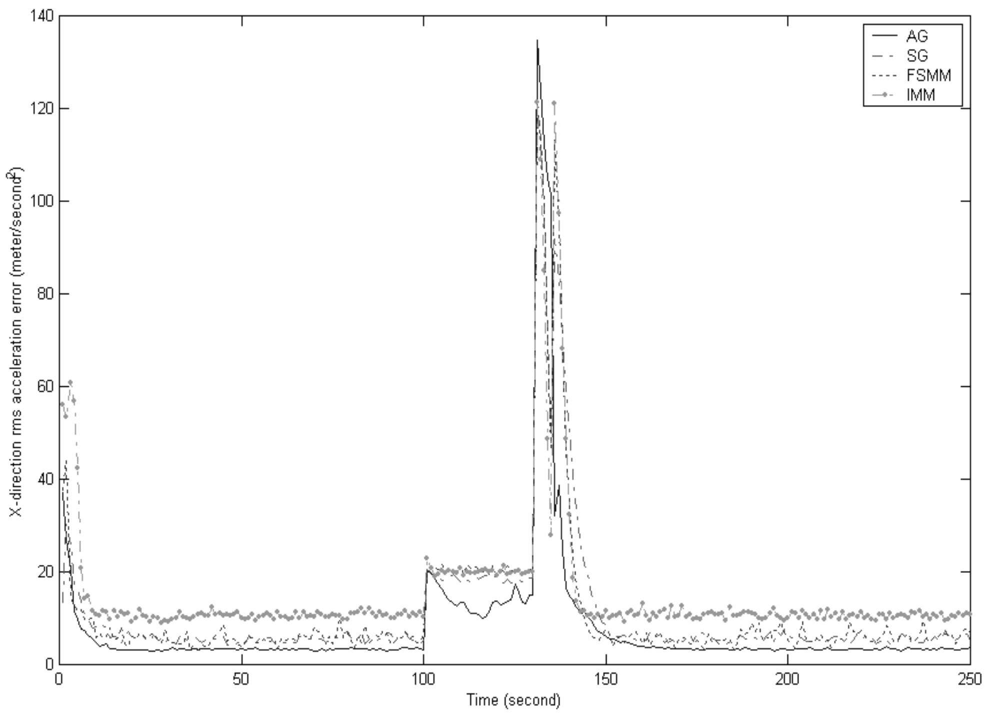

Fig. 11. The RMS errors in acceleration with $\sigma_x = \sigma_y$ =100 m, 500 Monte Carlo runs, Example 2.

V. CONCLUSIONS

Based on the variable-structured MM estimation concept and covariance matching technique, two VSMM algorithms (SGMMA and AGMMA) for maneuvering target radar tracking have been studied in this paper. The presented VSMM approaches, the usual FSMMA, and the IMM method have been evaluated and compared over different test scenarios. These new approaches have strong adaptive ability and higher accuracy in tracking maneuvering and non-maneuvering target. The simple structure of the algorithms makes it easy to implement for on-line processing. Simulation results have shown that during maneuvers the VSMMA provides better tracking characteristics compared with the FSMMA and IMM method, and at the same time they require less computation load.

Finally, the overall conclusion is that for the considered highly maneuvering target tracking problem, the variable structure approach to MM estimation can provide a preferable means of new and more efficient tracking algorithm. Furthermore, regarding the application of sustained maneuvering target tracking, the SGMMA provides better accuracy than AGMMA, but in cases of uncertainty about target maneuvering accelerations, the AGMMA is the better choice.

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