Prediction-based Interacting Multiple Model Estimation Algorithm for Target Tracking with Large Sampling Periods

Jon Ha Ryu, Du Hee Han, Kyun Kyung Lee, and Taek Lyul Song*

Abstract: An interacting multiple model (IMM) estimation algorithm based on the mixing of the predicted state estimates is proposed in this paper for a right continuous jump-linear system model different from the left-continuous system model used to develop the existing IMM algorithm. The difference lies in the modeling of the mode switching time. Performance of the proposed algorithm is compared numerically with that of the existing IMM algorithm for noisy system identification. Based on the numerical analysis, the proposed algorithm is applied to target tracking with a large sampling period for performance comparison with the existing IMM.

Keywords: Noisy system identification, prediction-based IMM, target tracking.

1. INTRODUCTION

Identification of systems with abrupt changes or unknown noise statistics plays a crucial role in controller design, failure detection, and maneuvering target tracking. When a single filter is used for system identification, accurate modeling is an important issue for reliable estimation performance. However, obtaining accurate modeling may be difficult in practice due to the lack of knowledge about the system and the practical limitations imposed by computational complexities. Multiple model estimation assuming that the system under consideration obeys one of a finite number of models is introduced in [2]. Dependence of identification performance on modeling can be weakened in this multiple model approach due to the probabilistic combination of the estimates generated from multiple filters. A bank of filters utilizing different models can also be applied to systems with switching models [3,4]. The multiple model estimation technique has evolved into the IMM algorithm [1]. The essential difference between the IMM algorithm and the previous multiple model estimation lies in the timing of hypotheses mixing, and it is known for its cost-effectiveness regarding computational complexity and performance. The IMM algorithm has been applied to a number of problems including air traffic control [5,18], target glint filtering [6], maneuvering target tracking [7], radar management [8], system noise identification [9], tactical ballistic missile tracking [12], and out-of-sequence measurements [19]. Recently, some modified versions of the IMM to improve estimation performance have been developed, such as the adaptive IMM algorithm [14], the reweighted IMM algorithm [15], and IMM estimation by smoothing [16,17].

The IMM algorithm was developed for a jump-linear system called the left-continuous system [10], in which the impact of the new mode starts right after the measurement sampling time. In this paper, a modified version of the IMM algorithm called the Prediction-based IMM (PBIMM) is developed for a jump-linear system in which the impact of the new mode starts just before the measurement sampling time such that the system becomes right-continuous. It is thought that the mode in nature is a continuous parameter that could be discretized and modeled in different ways. Moreover, it is found in this paper that the mode change time difference leads the PBIMM to have a different algorithm from the IMM and to reveal a different performance in noisy system identification and target tracking in an active sonar application. The PBIMM consists of 4 steps: prediction, interaction after mode change, measurement update, and combination. The order of the interaction and prediction steps is changed from that of the IMM algorithm. It is found that the PBIMM and the IMM algorithms are identical if the Markovian parameters defining the mode state are only related to the meas-

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urement equation. However, the algorithms are different if the Markovian parameters are involved in the system dynamic equation.

The PBIMM is applied to noisy system identification problems, and the performance is compared numerically with that of the IMM. Motivated by the numerical analysis, the PBIMM is further applied to target tracking by an active sonar with a large sampling period. The results indicate that the PBIMM outperforms the IMM and so could be used in practice for active sonar systems that require large sampling periods and yet need to produce accurate enough target state estimates.

2. DEVELOPMENT OF THE PBIMM

The jump-linear system model for development of the IMM algorithm [1,10] is described in (1) where the mode at time k, M_k, is assumed to be a Markovian parameter among the possible N modes with known mode transition probabilities.

$$\begin{aligned} x_k &= \Phi(M_k)x_{k-1} + B(M_k)w_{k-1}(M_k) \\ &\quad w_{k-1}(M_k) \sim N(b(M_k), Q(M_k)), \\ z_k &= H(M_k)x_k + v_k(M_k) \\ &\quad v_k(M_k) \sim N(c(M_k), R(M_k)). \end{aligned} \tag{1}$$

It is also assumed that the mode M_k is in effect for $t_{k-1}^+ \le t < t_k^+$ such that the mode jump process is assumed left-continuous (i.e., the impact of the new mode starts at t_k^+) [10]. The key feature of the IMM algorithm is mixing multiple models using mode probability in order to alleviate dependence of accuracy of target dynamic models and filter performance. As the sampling period becomes large, filter performance is seriously influenced by model accuracy. The alleviation of model dependence of the IMM algorithm may have a negative effect on filter performance when one of the models of the IMM algorithm matches with real target motion for tracking systems with large sampling periods. It is expected to have better filter performance by reducing uncertainty of prediction through performing the interacting step after the prediction step rather than vice versa. In order to implement the above assertion, the mode jump process could be modeled in a different way. The system model used in this paper is jump-linear, and the mode M_k is in effect for $t_k^- \le t < t_{k+1}^-$. The proposed system dynamic model is expressed as

$$\begin{aligned} x_k &= \Phi(M_{k-1})x_{k-1} + B(M_{k-1})w_{k-1}(M_{k-1}) \\ &\quad w_{k-1}(M_{k-1}) \sim N(b(M_{k-1}), Q(M_{k-1})), \\ z_k &= H(M_k)x_k + v_k(M_k) \\ &\quad v_k(M_k) \sim N(c(M_k), R(M_k)), \end{aligned} \tag{2}$$

where Φ, B, b, Q, H, c and R are considered to vary within a finite set. It is assumed that v_k and w_k are mutually independent Gaussian noise sequences and uncorrelated with x_0. In (2), the state x_k is considered as a propagated variable influenced by the mode M_{k-1} and the mode is allowed to change to M_k just before the measurement sampling time $t = t_k$; however, M_k does not influence x_k.

The difference between models (1) and (2) lies in model switch time. In the IMM algorithm which utilizes (1), the mode is modeled to switch its value right after the measurement sampling time while in this paper, the mode is modeled to switch just before the measurement sampling time.

The mode or hypothesis corresponding to the ith Markovian parameter is denoted as the mode state M^i. A cycle of recursions for the evolution of the conditional probability density functions in the development of the IMM algorithm [1] is summarized as

$$p(x_{k-1} \mid M_{k-1}^i, Z_{k-1}) \xrightarrow{\text{mode change, interacting}} p(x_{k-1} \mid M_k^i, Z_{k-1}) \xrightarrow{\text{prediction}} p(x_k \mid M_k^i, Z_{k-1}) \xrightarrow{\text{update}} p(x_k \mid M_k^i, Z_k) \tag{3}$$

where $Z_k = \{z_1, z_2, \cdots, z_k\}$. In the above, the interacting step that is unique in the IMM algorithm enables the mixing of the estimates in a cost-effective way while enhancing the performance compared to the other algorithms with similar computational complexities [1]. Detailed derivation of the IMM algorithm is referred to [1]. Now, the evolution of the conditional density functions for the system model of (2) should be modified to utilize the predicted estimates rather than the measurement-updated estimates in the interacting step such as

$$p(x_{k-1} \mid M_{k-1}^i, Z_{k-1}) \xrightarrow{\text{prediction}} p(x_k \mid M_{k-1}^i, Z_{k-1}) \xrightarrow{\text{mode change, interacting}} p(x_k \mid M_k^i, Z_{k-1}) \xrightarrow{\text{update}} p(x_k \mid M_k^i, Z_k). \tag{4}$$

Let $\hat{x}_{k-1}^i$ and $\hat{P}_{k-1}^i$ represent the conditional mean and covariance under the mode M_{k-1}^i given Z_{k-1} such as

$$p(x_{k-1} \mid M_{k-1}^i, Z_{k-1}) \sim N(\hat{x}_{k-1}^i, \hat{P}_{k-1}^i), \tag{5}$$

then the prediction step of (4) results in the predicted state estimation algzorithm of a Kalman filter as one can see from the dynamic equation of (2) and $p(x_k \mid M_{k-1}^i, Z_{k-1})$ satisfies

$$p(x_k \mid M_{k-1}^i, Z_{k-1}) \sim N(\bar{x}_k^i, \bar{P}_k^i). \quad (6)$$

To derive a representation of the interacting step of (4), the following equation is introduced from the Bayes formula

$$p(x_k \mid M_k^i, Z_{k-1}) = \frac{p(x_k, M_k^i \mid Z_{k-1})}{\mathrm{P}\{M_k^i \mid Z_{k-1}\}}, \quad (7)$$

where the probability of M_k^i for given Z_{k-1}, $\mathrm{P}\{M_k^i \mid Z_{k-1}\}$ is calculated by the Chapman-Kolmogorov equation as

$$\mathrm{P}\{M_k^i \mid Z_{k-1}\} = \sum_{j=1}^{N} \pi_{ji} \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\}, \quad (8)$$

where N is the total number of the modes under consideration and where $\pi_{ji} = \mathrm{P}\{M_k^i \mid M_{k-1}^j\}$ is the mode transition probability from M_{k-1}^j to M_k^i.

The numerator of (7) can be expressed from the total probability theorem as

$$\begin{aligned} &p(x_k, M_k^i \mid Z_{k-1}) \\ &= \sum_{j=1}^{N} p(x_k, M_k^i \mid M_{k-1}^j, Z_{k-1}) \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\} \\ &= \sum_{j=1}^{N} p(x_k \mid M_{k-1}^j, Z_{k-1}) \pi_{ji} \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\}, \end{aligned} \quad (9)$$

where the fact that for the system dynamic model of (2), x_k is independent of M_k^i for the given M_{k-1}^j is used.

If we assume that $p(x_k \mid M_k^i, Z_{k-1})$ of (7) satisfies

$$p(x_k \mid M_k^i, Z_{k-1}) \sim N(\tilde{x}_k^i, \tilde{P}_k^i), \quad (10)$$

then $\tilde{x}_k^i$ and $\tilde{P}_k^i$ are obtained from (6), (8) and (9) as

$$\tilde{x}_k^i = \frac{\sum_{j=1}^{N} \bar{x}_k^j \pi_{ji} \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\}}{\sum_{j=1}^{N} \pi_{ji} \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\}}, \quad (11)$$

$$\tilde{P}_k^i = \frac{\sum_{j=1}^{N} (\bar{P}_k^j + (\bar{x}_k^j - \tilde{x}_k^i)(\bar{x}_k^j - \tilde{x}_k^i)^T) \pi_{ji} \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\}}{\sum_{j=1}^{N} \pi_{ji} \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\}}.$$

Each of N pairs $\tilde{x}_k^i$ and $\tilde{P}_k^i$ is used as input to a Kalman filter based on the mode M_k^i to yield $\hat{x}_k^i$, $\hat{P}_k^i$ in the update process of (4) such that

$$p(x_k \mid M_k^i, Z_k) \sim N(\hat{x}_k^i, \hat{P}_k^i). \quad (12)$$

Similar to the IMM algorithm of [1], the states and covariances are combined for output purpose only from

$$\begin{aligned} \hat{x}_k &= \sum_{i=1}^{N} \hat{x}_k^i \mathrm{P}\{M_k^i \mid Z_k\}, \\ \hat{P}_k &= \sum_{i=1}^{N} (\hat{P}_k^i + (\hat{x}_k^i - \hat{x}_k)(\hat{x}_k^i - \hat{x}_k)^T) \mathrm{P}\{M_k^i \mid Z_k\}, \end{aligned} \quad (13)$$

where the mode probability $\mathrm{P}\{M_k^i \mid Z_{k-1}\}$ is updated by

$$\mathrm{P}\{M_k^i \mid Z_k\} = \frac{p(z_k \mid M_k^i, Z_{k-1}) \sum_{j=1}^{N} \pi_{ji} \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\}}{\sum_{h=1}^{N} p(z_k \mid M_k^h, Z_{k-1}) \sum_{j=1}^{N} \pi_{jh} \mathrm{P}\{M_{k-1}^j \mid Z_{k-1}\}}. \quad (14)$$

Note that $p(z_k \mid M_k^i, Z_{k-1})$ in (14) satisfies

$$p(z_k \mid M_k^i, Z_{k-1}) = \frac{1}{\left|2\pi \tilde{S}_k^i\right|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(z_k - H\tilde{x}_k^i)^T (\tilde{S}_k^i)^{-1} (z_k - H\tilde{x}_k^i)\right), \quad (15)$$

where $\tilde{S}_k^i$ is defined as $H\tilde{P}_k^i H^T + R$. If we denote b as a parameter in the mode state M^i to be identified, then the estimate of b at $t = t_k$ can also be obtained from

$$\hat{b}_k = \sum_{i=1}^{N} b^i \mathrm{P}\{M_k^i \mid Z_k\}, \quad (16)$$

where M_k^i is the ith mode assuming the value of b as b^i. The resulting algorithm called the PBIMM can be illustrated as Fig. 1.

The PBIMM is the same as the IMM if the Markovian parameters are only involved in the measurement equation so that H, c, and R are designated to the mode state $M^j, j = 1, 2, \cdots, N$. However, it was found that the PBIMM and the IMM are different if the mode set is defined in the system dynamics so that Φ, B, b and Q are designated to the mode states. The latter case has many important applications such as fault detection, maneuvering target tracking, and process noise identification. As

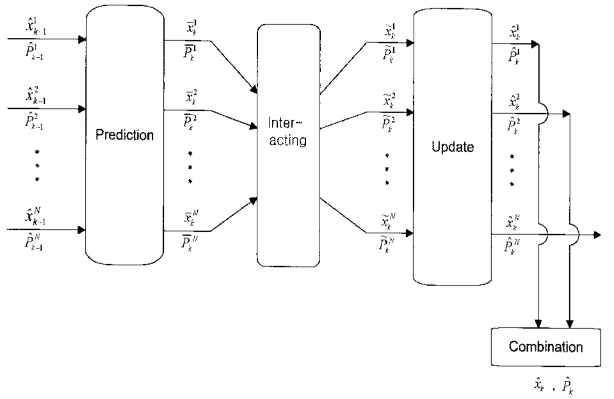

Fig. 1. Schematic diagram of the PBIMM.

shown in the above derivation, if the dimension of the state vector and the number of modes are the same in both algorithms, the PBIMM has identical computational complexity to the existing IMM. This is due to the fact that both algorithms consist of identical interacting, prediction and update steps; however, the order of steps and the inputs to each step are merely changed. For example, the updated state estimate $\hat{x}_{k-1}^{j}$ of the IMM is replaced by the predicted state estimate $\bar{x}_{k}^{j}$ of the PBIMM as the input to the interacting step.

3. SIMULATION RESULTS

In the first part of this section, performance of the PBIMM is tested and compared with that of the IMM when the process noise of a second-order linear system is to be identified. The system is described by [9]

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{k+1} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k + \begin{bmatrix} \frac{T^2}{2} \\ T \end{bmatrix} w_k, \tag{17}$$
$$z_k = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k + v_k.$$

The stationary process noise w_k is a Gaussian noise sequence with unknown mean and variance whereas the measurement noise v_k is a zero-mean Gaussian noise sequence with $R=1$. Firstly, the unknown mean is identified by the PBIMM with the two possible modes $M^1 : w_k \sim N(1,1)$, and $M^2 : w_k \sim N(10,1)$. The sampling period $T=1$ is used as [9]. The transition probability matrix of the two-mode system used is

$$\{\pi_{ji}\} = \begin{bmatrix} 0.98 & 0.02 \\ 0.02 & 0.98 \end{bmatrix}, \tag{18}$$

Table 1. Identification of process noise mean with $b^1 = 1$ and $b^2 = 10$.

true mean	1	1.3	1.5	2
IMM	1.120	1.192	1.260	1.522
PBIMM	1.270	1.333	1.403	1.710
true mean	3	4	5	6
IMM	2.534	3.794	4.956	6.052
PBIMM	2.817	3.976	5.007	5.976
true mean	7	8	9	9.5
IMM	7.194	8.427	9.458	9.737
PBIMM	7.023	8.164	9.264	9.581
true mean	9.7	10	·	·
IMM	9.808	9.882	·	·
PBIMM	9.656	9.724	·	·

while the two initial mode probabilities were both set to 0.5 since no prior information was available concerning the modes. The process noise mean was estimated according to the parameter identification algorithm expressed in (16). Table 1 is a summary of the results of a series of Monte Carlo simulation runs as the true mean value is between 1 and 10. Each result is the average quantity obtained from 100 simulation runs with 40 sampling periods per each run.

The results indicate that the PBIMM performs better than the IMM except in the cases where the true mean becomes very close to the lower and upper bounds b^1 and b^2 and where the true mean becomes close to the average value of b^1 and b^2. When the true mean is close to the average of b^1 and b^2, the PBIMM and the IMM show almost identical results.

Hence, it is noteworthy that the PBIMM generates more accurate estimates than those of the IMM for the wide range of b as illustrated in Table 1, and that the PBIMM could be more usefully applied in practice since the exact values of the upper and lower bounds are not exactly known in general.

Next, the process noise variance Q is to be identified with the two possible modes $M^1 : w_k \sim N(0,1)$, and $M^2 : w_k \sim N(0,10)$. The other simulation conditions are equivalent to the previous case. The results are summarized in Table 2.

The results indicate that the PBIMM performs better than the IMM except in the cases where the true process noise variance approaches the lower and upper bounds expressed as Q^1 and Q^2, respectively. The results also indicate that the PBIMM may produce more accurate estimates of Q in practical

Table 2. Identification of process noise variance with $Q^1=1$ and $Q^2=10$.

true variance Q	1	3	5	7	10
IMM	2.213	5.292	6.909	7.836	8.457
PBIMM	2.288	5.20	6.756	7.671	8.305

applications as the exact values of the upper and lower bounds are not known, and the bounds are filter design parameters.

The influence of the sampling period T on estimating the process noise mean b is analyzed next. The unknown mean is identified with the two possible modes $M^1 : w_k \sim N(1,1)$, and $M^2 : w_k \sim N(10,1)$ for various values for $T \in \{0.1, 0.5, 1, 1.5, 2\}$. Fig. 2. is a summary of time averages of the estimates of b by the PBIMM and the IMM obtained from 100 runs of Monte Carlo simulation. The results for $T=1$ are referred to in Table 1.

Table 1 and Fig. 2 indicate that the performance of the IMM is similar to the performance of the PBIMM for identifying most of the true mean values when T is small. However, the PBIMM performs better than the IMM when T becomes large except in the cases where the true mean becomes model values for the filters. As the process noise mean b can be considered as the target acceleration, the above results motivate applications of the PBIMM to target tracking with a large sampling period as is seen in active sonar practices.

The first example in this section is extended to 2-dimensional underwater target tracking by an active sonar system which has a relatively large sampling period. The discretized system equations for maneuvering target tracking are described by

$$\begin{aligned} x_{k+1} &= \Phi x_k + \Gamma(a_k + w_k), \\ z_k &= H x_k + G v_k, \end{aligned} \tag{19}$$

where the state x_k consists of target position and

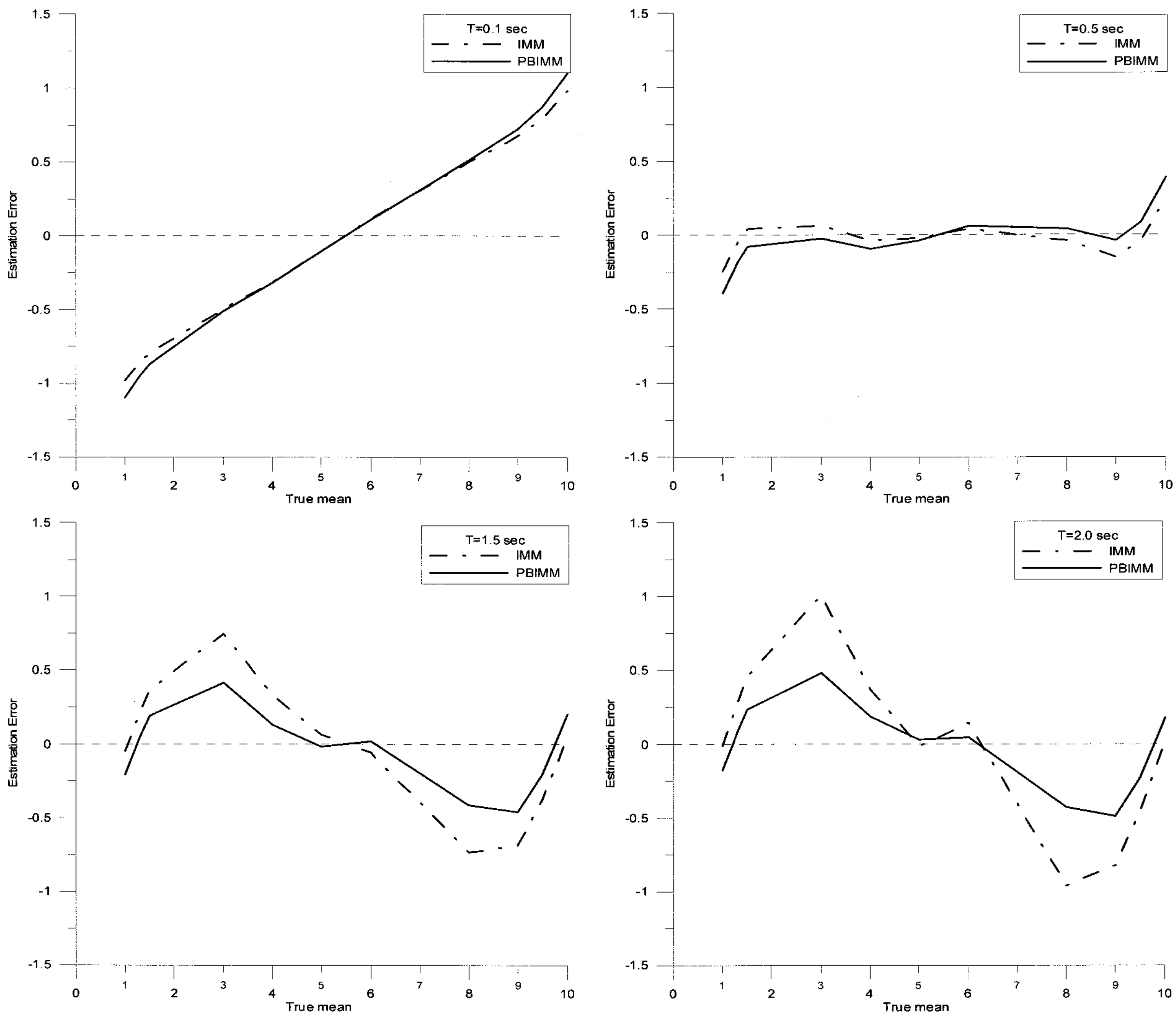

Fig. 2. Estimation error of process noise mean for various sampling periods.

velocity components in X and Y axes such that $x_k = (X, Y, \dot{X}, \dot{Y})_k^T$, w_k is a zero-mean white Gaussian process noise vector with covariance Q, and v_k is a zero-mean measurement noise vector with covariance R. System matrices for (19) are defined as

$$\Phi = \begin{bmatrix} I_2 & TI_2 \\ 0 & I_2 \end{bmatrix}, \quad \Gamma = \begin{bmatrix} T^2/2 \, I_2 \\ TI_2 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \quad G = I_2, \tag{20}$$

and $a_k = (\ddot{X}, \ddot{Y})_k^T$ is the target acceleration vector. The PBIMM algorithm approximates the evolution of the target true acceleration within a finite set of acceleration values. The 4 modes describing 2-dimensional target acceleration vectors are selected as $M_1 = (0.05, 0.05)^T (\text{m}/\text{sec}^2)$, $M_2 = (-0.05, 0.05)^T$ (m/sec^2), $M_3 = (-0.05, -0.05)^T$ (m/sec^2) and $M_4 = (0.05, -0.05)^T (\text{m}/\text{sec}^2)$. For the target tracking problem, $Q = 0.05^2 I_2 (\text{m}/\text{sec}^2)^2$, $R = 10^2 I_2 (\text{m})^2$ are used, the sampling period is chosen to be 13sec, and the mode transition probability matrix is selected to be

$$\{\pi_{ji}\} = \begin{bmatrix} 0.85 & 0.05 & 0.05 & 0.05 \\ 0.05 & 0.85 & 0.05 & 0.05 \\ 0.05 & 0.05 & 0.85 & 0.05 \\ 0.05 & 0.05 & 0.05 & 0.85 \end{bmatrix}. \tag{21}$$

Note that the measurement noise covariance results in a standard deviation of 14.14m in the range direction error. The initial position of the target is $(6\text{km}, 6\text{km})^T$ and the initial velocity of the target is $(0, -3\text{m/sec})^T$. For the time interval $0\,\text{sec} \le t < 720$ sec, the target moves in a circular path of radius 344m with a constant velocity and acceleration of 0.026 m/sec^2. The target trajectory is shown in Fig. 3.

Figs. 4-6 show the RMSE values of 1,000 runs of Monte Carlo simulation resulting from employing the IMM and the proposed PBIMM. The results indicate that the PBIMM outperforms the IMM for target position, velocity, and acceleration estimation. The results indicate that the PBIMM can be used for practical target tracking with large sampling periods as required in active sonar systems and sonar resource management practices [11].

Finally, the PBIMM and the IMM algorithms with

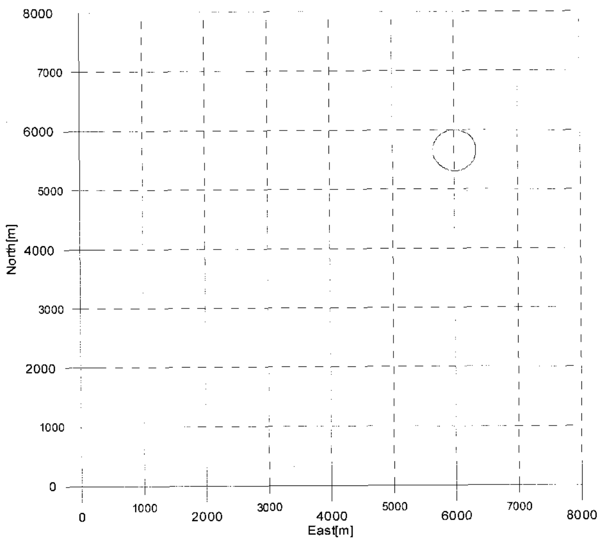

Fig. 3. Target trajectory.

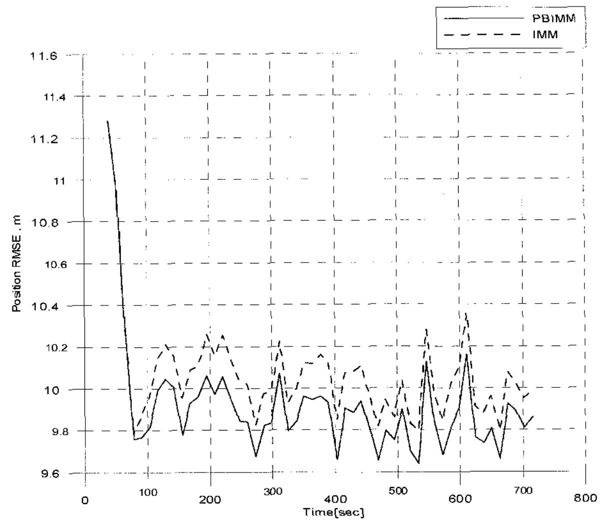

Fig. 4. RMSE of target position estimates.

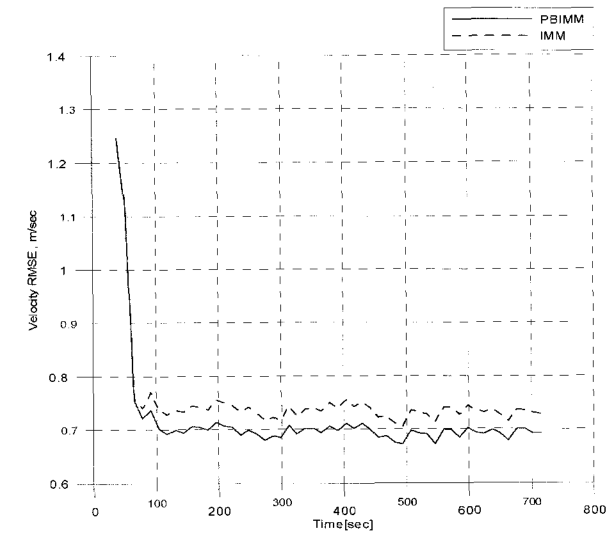

Fig. 5. RMSE of target velocity estimates.

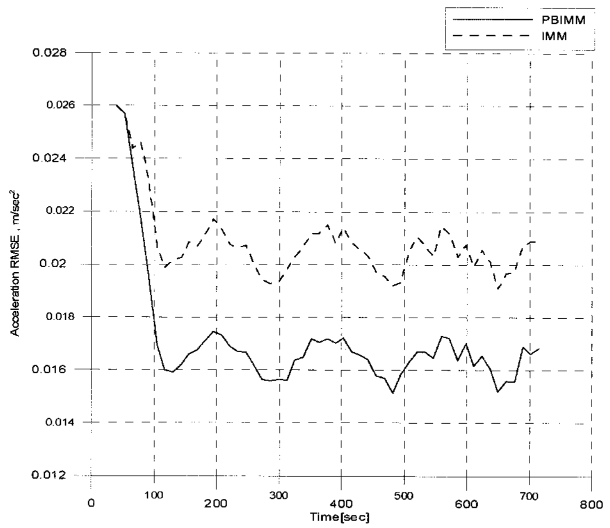

Fig. 6. RMSE of target acceleration estimates.

two different dynamic models are applied to underwater active sonar target tracking. The dynamic models used in the simulation study are the constant velocity (CV) model and the constant turn rate (CTR) model. The CV model employs the discretized system equation of (19) with $a_k = 0$, and the system matrices are the same as described in (20). The state of the CTR model consists of target position, velocity, and acceleration components, and the system equations are expressed in the same form as the CV model, but with different dimensions. The system matrices are expressed as follows [20,21].

$$\Phi = \begin{bmatrix} I_2 & \frac{\sin\omega T}{\omega} I_2 & \frac{1-\cos\omega T}{\omega^2} I_2 \\ O_2 & \cos\omega T I_2 & \frac{\sin\omega T}{\omega} I_2 \\ O_2 & -\omega\sin\omega T I_2 & \cos\omega T I_2 \end{bmatrix},$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad G = I_2, \tag{22}$$

$$\Gamma = \begin{bmatrix} \frac{\omega T - \sin\omega T}{\omega^3} I_2 \\ \frac{1-\cos\omega T}{\omega^2} I_2 \\ \frac{\sin\omega T}{\omega} I_2 \end{bmatrix},$$

where ω is the turn rate. For this target tracking problem, $R = 10^2 I_2(\mathrm{m})^2$, $Q_{CV} = 0.01^2 I_2(\mathrm{m/sec}^2)^2$, $Q_{CTR} = 0.005^2 I_2(\mathrm{m/sec}^3)^2$ are used and the mode transition probability matrix is selected to be

$$\{\pi_{ji}\} = \begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix}. \tag{23}$$

The target is assumed as a submarine, which executes an evasive maneuver to avoid a situation of being tracked by a target motion analysis scheme. The initial position of the target is $(6\mathrm{km}, 6\mathrm{km})^T$, and the target is initially moving in a straight line with a constant speed of $3(\mathrm{m/sec})$ with -67.5° of heading angle from the Y-axis. The target moves with an initial course of -67.5° for $0\,\mathrm{sec} \le t < 50\mathrm{sec}$, and then the target executes a periodic motion with $\omega = \pm 1$ (deg/sec) with a switching period of 135 seconds. Note that if an active sonar system is used to detect a target located near 10km from the system, a sampling period of 13sec is required. The target trajectory is depicted in Fig. 7.

Figs. 8-10 show the results extracted from 1,000 Monte Carlo simulation runs to demonstrate the superior performance of the proposed PBIMM by comparison with the IMM. Listed in these figures are

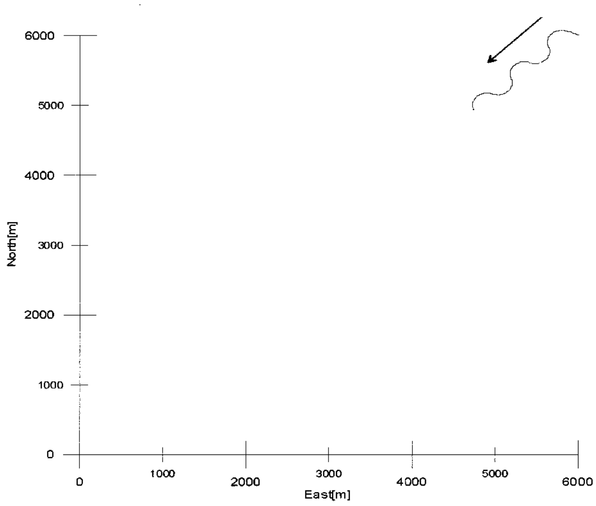

Fig. 7. Target trajectory.

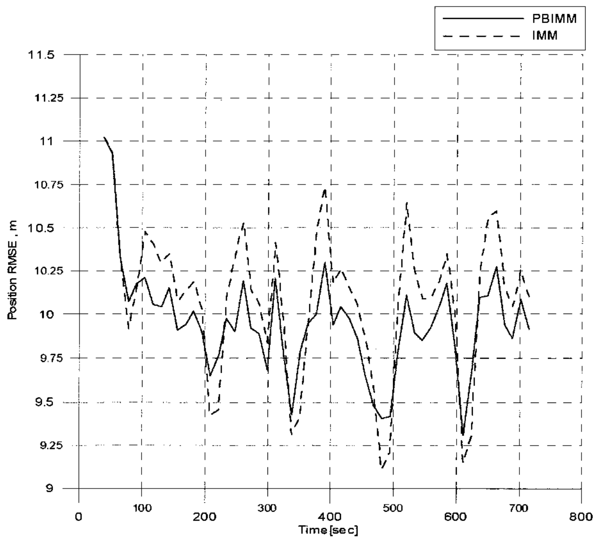

Fig. 8. RMSE of target position estimates.

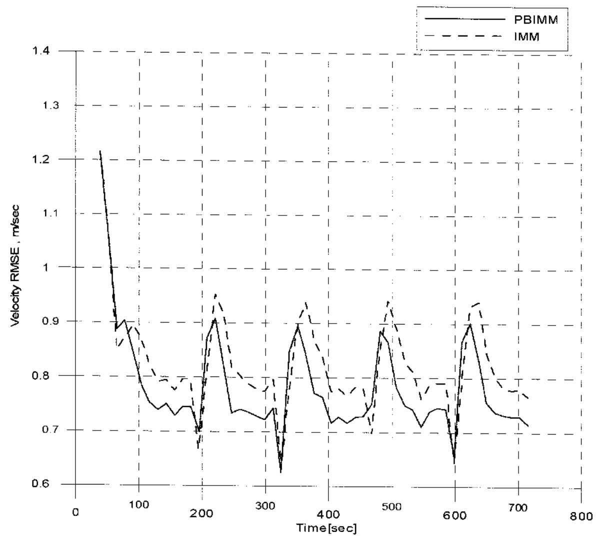

Fig. 9. RMSE of target velocity estimates.

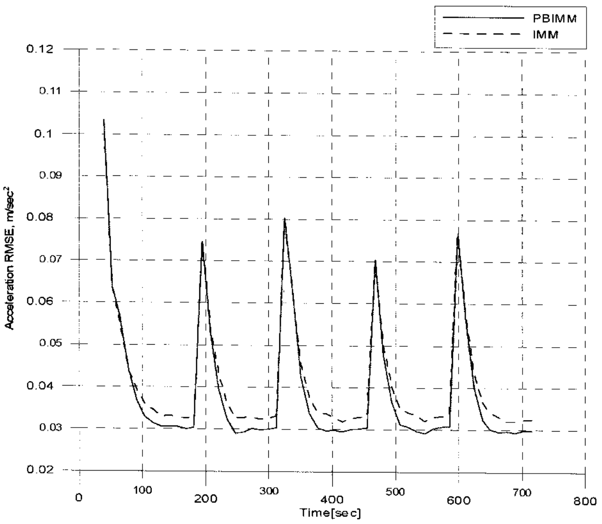

Fig. 10. RMSE of target acceleration estimates.

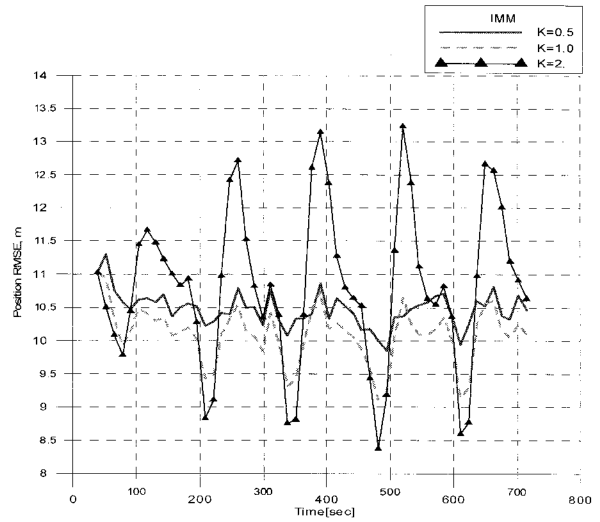

Fig. 11. RMSE of target position estimates of the IMM algorithm.

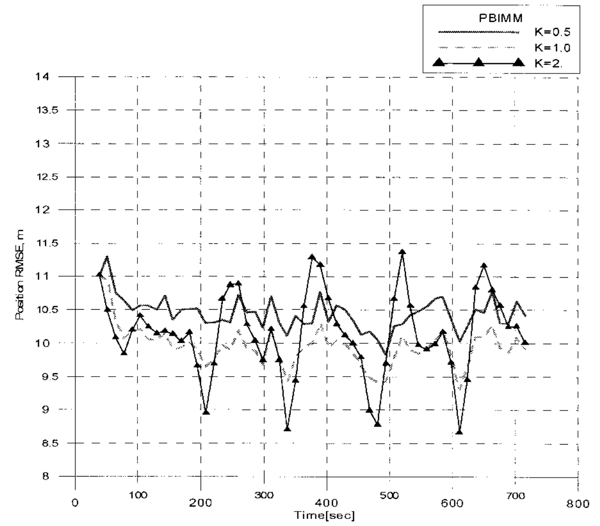

Fig. 12. RMSE of target position estimates of the PBIMM algorithm.

the RMSE values of the estimates of the target position, velocity, and acceleration. The results indicate that the proposed PBIMM has a superior performance to the IMM, and that it has advantages in calculating future target positions such as are required in combat management systems.

In addition to these results, Figs. 11 and 12 show the sensitivities of the IMM and the PBIMM to the same variations of R. The scalar k is a filter parameter used in filter algorithms such that the filters assume that the measurement noise covariance is k^2R instead of the true value of R.

The simulation results show that the PBIMM is less sensitive to the filter parameter since the RMSE values of the IMM are much more widely dispersed than those of the PBIMM as k varies, which indicates that the PBIMM has some practical advantages since the true measurement noise covariance may not be available in diverse underwater tracking environments.

4. CONCLUSION

The PBIMM algorithm based on the mixing of the predicted state estimates is developed and applied to process noise identification of a linear system and a 2-dimensional target tracking with a large sampling period. Similar to the existing IMM algorithm, the PBIMM algorithm is cost effective regarding computational complexity and performance compared to the other multiple model approaches.

The PBIMM produces the same results as the IMM if the Markovian parameters are only involved in the system measurement while producing different results if the Markovian parameters are involved in the system dynamics. A study of Monte Carlo simulation runs indicates that the PBIMM produces more accurate estimates of mean and covariance of process noise than the IMM if the sampling period becomes larger while producing a similar performance for small sampling periods. Based on the numerical analysis, the PBIMM is applied to underwater target tracking with an active sonar system of which the sampling period is 13sec. The results of the Monte Carlo simulation runs indicate that the PBIMM outperforms the IMM in this application. It is also shown that the PBIMM has more freedom than the IMM to select filter parameter values for maneuvering target tracking such that this burden can be alleviated for filter parameter tuning. A series of simulation studies shows that the PBIMM is a viable solution to target tracking systems operated with large sampling periods.

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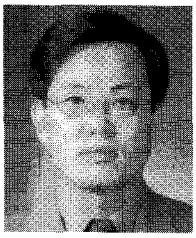

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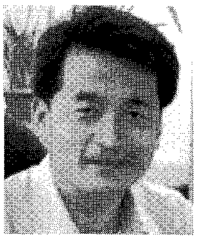

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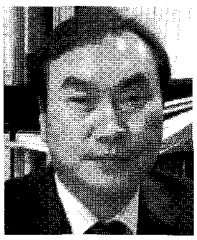

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