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# Maneuvering Target Tracking Using Error Monitoring

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## Abstract

This work is concerned with the problem of tracking a maneuvering target. In this paper, an error monitoring and recovery method of perception net is utilized to improve tracking performance for a highly maneuvering target. Many researches have been performed in tracking a maneuvering target. The conventional Interacting Multiple Model (IMM) filter is well known as a suboptimal hybrid filter that has been shown to be one of the most cost-effective hybrid state estimation scheme. The subfilters of IMM can be considered as fusing its initial value with new measurements. This approach is also shown in this paper. Perception net based error monitoring and recovery technique, which is a kind of geometric data fusion, makes it possible to monitor errors and to calibrate possible biases involved in sensed data and extracted features. Both detecting a maneuvering target and compensating the estimated state can be achieved by employing the properly implemented error monitoring and recovery technique. The IMM filter which employing the error monitoring and recovery technique shows good tracking performance for a highly maneuvering target as well as it reduces maximum values of estimation errors when maneuvering starts and finishes. The effectiveness of the proposed method is validated through simulation by comparing it with the conventional IMM algorithm.

## 1. Introduction

The problem of tracking a maneuvering target has received a great deal of attention. Many researches have been performed in tracking a maneuvering target. Since Singer [1] proposed a target model including maneuvering motion in 1970, many researches have been performed in tracking a maneuvering target. We can outline techniques representative of two general approaches to maneuver adaptive filtering. The first approach is to detect maneuver and cope with maneuver. For this approach, Bogler [2] and Whang, *et. al.*[3] proposed a input estimation filter, Bar-Shalom, *et. al.*[4] proposed a variable dimension filter, and Park, *et. al.*[5] proposed a variable dimension with input estimation filter. The second approach is to use multiple dynamic model. For this approach, Blom and Bar-Shalom [6] proposed an interacting multiple model (IMM) filter.

The Interacting Multiple Model (IMM) [6-8] estimator is a suboptimal hybrid filter that has been shown to be one of the most cost-effective hybrid state estimation schemes. The value of hybrid models for tracking algorithm is that the occurrence of target maneuvers can be explicitly included in the kinematic equations through regime jumps.

But the model probabilities of IMM filter trend to be slowly adapted from the nonmaneuver mode to maneuver mode or from maneuver to nonmaneuver, although sudden maneuver can take place in the true system. This is why the model probability is dependent on past model probabilities. In order to track a suddenly and highly maneuvering target, the technique which combines IMM algorithm with error monitoring and recovery technique of perception net is proposed in this paper.

The perception net [9, 10], as a structural representation of the sensing capabilities of system, is formed by the interconnection of logical sensors with three types of modules: feature transformation module (FTM), data fusion module (DFM), and constraint satisfaction module (CSM). Observing the output and input of DFM, we can detect an error of input data. Error monitoring and recovery technique based on this function make it possible to detect and identify error, and to calibrate possible biases involved in sensed data and extracted features. Both detecting maneuver and compensating the estimated state can be achieved by employing the properly implemented error monitoring and recovery technique. The IMM filter which employs the error monitoring and recovery technique shows good tracking performance for a highly maneuvering target as well as reduces maximum values of estimation errors when maneuvering starts and finishes

For its recursive structure and capability of sequential data processing, the Kalman filter is widely used as a tracking filter to estimate position, velocity, and acceleration of a target in real-time. If Kalman filter is examined in view of structure, it is that the current predicted state, which is calculated from the state at the previous time, is combined with the measurement that is acquired by physical sensor at current time [11, 12]. Perception net based geometric data fusion is the same as Kalman filtering, and in order to introduce perception net in target tracking, we also prove it through algebraic approach.

## 2. Problem Formulation

Consider a dynamical system (target model) of standard and linear discrete time-invariant measurement equation.

$$x_t(k+1) = F_t x_t(k) + v_t(k) \quad (1)$$

$$z(k) = Hx(k) + w(k) \quad (2)$$

where $x_t(k)$ is an $n$-dimensional state vector at time $k$ for model $t$, $z(k)$ is an $m$-dimensional measurement vector at time $k$, and $v(k)$ and $w(k)$ are zero-mean, mutually independent white Gaussian noise vectors with covariance matrices $Q(k)$ and $R(k)$, respectively. The state vector would typically include position and velocity variables, as well as other information that relates to the specific type of platform being tracked. It is assumed that state vector includes acceleration variables in here.

We focus here on the IMM filter for tracking a maneuvering target. We briefly review the IMM filter. The basic assumption of the IMM filter is that the system obeys one of a finite number of models with known parameters and model switches occur according to a Markov chain with known transition probabilities. In this approach the state estimate is computed under each possible model hypothesis as many filters as the number of assumed models with each filter using a different combination of the previous model conditioned estimates.

One cycle of the IMM filter consists of the following three steps [7, 8].

- *Step 1:* Mixing of estimates from previous time (interacting).

$$\hat{x}_{0t}(k-1|k-1) = \sum_{s=1}^{N} \hat{x}_s(k-1|k-1)\mu_{s|t}(k-1|k-1), \quad (3)$$

and

$$\begin{aligned} P_{0t}(k-1|k-1) = & \sum_{s=1}^{N} \mu_{s|t}(k-1|k-1)\{P_s(k-1|k-1) \\ & + [\hat{x}_s(k-1|k-1) - \hat{x}_{0t}(k-1|k-1)] \\ & \times [\hat{x}_s(k-1|k-1) - \hat{x}_{0t}(k-1|k-1)]^T\}, \\ & t = 1, 2, \cdots, N \end{aligned} \quad (4)$$

where

$$\mu_{s|t}(k-1|k-1) = \frac{1}{\bar{c}_t}\Theta_{s|t}\mu_s(k-1) \quad (5)$$

$$\bar{c}_t \equiv \sum_{s=1}^{N} \Theta_{s|t}\mu_s(k-1)$$

and $\Theta_{s|t}$ is the assumed Markov model switching probability from model $s$ at previous time to model $t$ at current time. $N$ is the number of subfilters of IMM filter. $\bar{c}_t$ is a normalization factor.

- *Step 2:* Kalman filtering.

$$\hat{x}_t(k|k-1) = F_t\hat{x}_{0t}(k-1|k-1) \quad (6)$$

$$\hat{x}_t(k|k) = \hat{x}_t(k|k-1) + G_t(k)r_t(k) \quad (7)$$

$$P_t(k|k-1) = F_tP_{0t}(k-1|k-1)F_t^T + Q_t(k-1) \quad (8)$$

$$P_t(k|k) = [I - G_t(k)H]\,P_t(k|k-1) \quad (9)$$

(residual)

$$r_t(k) = z(k) - \hat{z}_t(k|k-1) \quad (10)$$

(predicted measurement)

$$\hat{z}_t(k|k-1) = H\hat{x}_t(k|k-1) \quad (11)$$

(residual covariance)

$$S_t(k) = HP_t(k|k-1)H_t^T + R(k) \quad (12)$$

(filer gain)

$$G_t(k) = P_t(k|k-1)H^TS_t(k)^{-1} \quad (13)$$

(likelyhood function)

$$\Lambda_t(k) = N(r_t(k); 0, S_t(k)) \quad (14)$$

(model probability)

$$\mu_t(k) = \frac{1}{c}\Lambda_t(k)\sum_{s=1}^{N}\Theta_{s|t}\mu_s(k-1) \quad (15)$$

where $c$ is a normalizing factor.

- *Step 3:* Combination.

$$\hat{x}(k|k) = \sum_{t=1}^{N} \hat{x}_t(k|k)\mu_t(k) \quad (16)$$

$$\begin{aligned} P(k|k) = \sum_{t=1}^{N} \mu_t(k)\,\{P_t(k|k) + [\hat{x}_t(k|k) - \hat{x}(k|k)] \\ \times [\hat{x}_t(k|k) - \hat{x}(k|k)]^T\} \end{aligned} \quad (17)$$

## 3. Perception Net

The perception net, as a structural representation of the sensing capabilities of system, is based on geometric data fusion. The perception net is formed by the interconnection of logical sensors with three types of modules: feature transformation module (FTM), data fusion module (DFM), and constraint satisfaction module (CSM). We briefly represent FTM, DFM, and error monitoring and recovery techinique.

It is assumed that noise is bounded by an uncertainty hyper-volume or ellipsoid, and that the size of uncertainty ellipsoid is small enough for a good linear approximation around the nominal point in feature transformation. Formally, we represent the uncertainty, $dx$, of a sensor value, $x$, as an ellipsoid of the following form.

$$dx^T\ W_x\ dx \leq 1 \quad (18)$$

where $W_x$ represents a symmetric weight matrix determining the size and shape of the ellipsoid.

The uncertainties propagate through input-output relationships between the input vector and the output vector of modules. Let us define the mapping relationship between the input vector, $x$, and the output vector, $y$, of FTM or a DFM. Then uncertainty propagation canbe approximated as the first order Jacobian relationship with assumption that $f$ is smooth and $dx$ is small, as follow

$$y = f(x, p), \quad (19)$$

$$y + dy = f(x + dx, p) \approx f(x, p) + \frac{\partial f}{\partial x}\Delta x, \quad (20)$$

$$dy \approx \frac{\partial f}{\partial x}dx = J(x, p)dx, \quad (21)$$

where $p$ represents a parameter vector associated with the module and $J(x, p)$ represents the Jacobian relationship between $dy$ and $dx$. The uncertainty of $x$ represented as an ellipsoid of (18) can now be propagated to the uncertainty of $dx$, represented as an ellipsoid in terms of $dy$, through (21). By substituting $dx = J^+(x,p)dy$, obtained from (21), to (18), we have

$$dy^T(J^+)^T\ W_x\ J^+dy \leq 1 \qquad (22)$$

where $J^+$ represents the pseudo-inverse of $J$. The symmetric weight matrix, $W_y$, is defined as follow

$$W_y \equiv (J^+)^T\ W_x J^+. \qquad (23)$$

Consider the data fusion as the geometric data combining. For simplicity, consider the two measurements, $x_1$ and $x_2$, defined respectively in the two measurement space, where their uncertainty bounds are defined by the weight matrices, $W_{x_1}$ and $W_{x_2}$, respectively. Geometric Data fusion method starts with defining the augmented space, $X = [x_1^T\ x_2^T]^T$ and $W_X = \mathrm{Diag}[W_{x_1}\ W_{x_2}]$, such that the measurement data is represented in an augmented space as $(X, W_X)$. Then the problem of fusing data is equivalent to find a point, $y$, on the constraint manifold, $x_1 = x_2$, defined in the $X$ space in such a way that the weighted distance between $y$ and $X$ is minimum. In other words, the problem of fusing $(x_1, W_{x_1})$ and $(x_2, W_{x_2})$ is equivalent to obtain $y$ to minimize $\frac{1}{2}\ \|y - X\|^2_{W_X}$.

More specifically, the output $y$ of module with $x_1$ and $x_2$ as its inputs can be determined as the vector that minimizes (for convenience, we define that $xi$ indicates $x_i$ whenever it is used as the subscript)

$$\sum_i \frac{1}{2}\ \|y - x_i\|^2_{W_{xi}}. \qquad (24)$$

Then $y$ that minimizes (24) is calculated by least square method as follow

$$y = (W_{x_1} + W_{x_2})^{-1}\,(W_{x1}x_1 + W_{x2}x_2). \qquad (25)$$

The uncertainty bound, $W_y$, associated with $y$ can be obtained by applying (21), (22), and (23) to (25), as follow

$$W_y = \left\{(AA^T + BB^T)^{-1}\right\}^T (AW_{x1}A^T + BW_{x2}B^T) \times (AA^T + BB^T)^{-1} \qquad (26)$$

where

$A \equiv (W_{x_1} + W_{x_2})^{-1}\,W_{x1}$, $B \equiv (W_{x_1} + W_{x_2})^{-1}\,W_{x2}$.

Simple perception net representation of a logical sensor system is displayed in Fig. 1. The propagation through FTM is from (18) to (23). The propagation through DFM is from (24) to (26). Perception net is proposed to combine sensors efficiently under multisensor environment. However, replacing physical sensor with logical sensor, we can apply the perception net to the problem of tracking a target under the single sensor. Whether the data are from the physical sensor or the logical sensor, this acquired data in the same measurement space can be combined. This is not inappropriate to the principle of perception net.

Error monitoring and recovery technique consists of three steps. The first step is to detect an error in input data by using the output of DFM. If the error is detected, then the second step is to identify the source(sensor) which making error. The third step is to replan the sensor with fault. The inconsistency among the input data of DFM

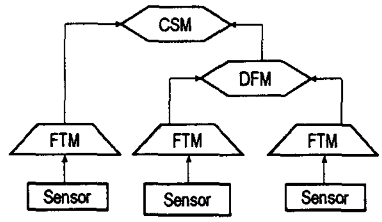


Fig. 1. A schematic illustration of a logical sensor system

can be evaluated based on the ellipsoidal representation of uncertainty bound: The input data of DFM are said to be inconsistent, if the ellipsoidal uncertainty bounds of input data have no common intersection. The existence of a common intersection among the input data can be evaluated by: if $\|y(k) - x_i(k)\|^2_{W_{xi}} \leq 1$, for $i = 1,\ 2$ with the output, $y(k)$, of DFM, then there exists a common intersection among the ellipsoidal uncertainty bound of $x_i(k)$.

The isolation of error sources can be done through the net hierarchy. By applying the above error detection method to DFMs, those logical sensors associated with DFMs can be classified either likely-in-error, unlikely-in-error, or possibly-in-error. These classifications are propagated through the net to extended the classifications to other logical sensors connected through the hierarchy. The cross-checking of these classifications propagated through the net hierarchy provides further isolation of errors. Once source are isolated, then the system take action to repair the errors and to recover from the error. The system needs to replan the task based on the isolated errors. But identification and replanning of error sources cannot be implemented in the general method but should be implemented in the suitable method to the circumstance.

## 4. Maneuvering Target Tracking Using Error Monitoring and Recovery Technique

To apply the perception net to tracking filter, we need to know how perception net is connected with Kalman filter. Covariance matrix of state vector in Kalman filter represents the size of a state uncertainty. Also inverse covariance matrix means the weighting matrix of state. It is shown to be true through Theorem 1.

*Theorem 1*: Let $x_1(k)$ be the predicetd state of Kalman filter, $x(k|k-1)$, and $x_2(k)$ be

$$x_2(k) \equiv H^T z(k). \qquad (27)$$

If the covariance matrices of state vector and measurement vector are nonsingular and $HH^T = I_{m\times m}$, then the output, $y$, of DFM with $x_1(k)$ and $x_2(k)$ as its inputs is same with the measurement update equation of Kalman filter using the predicted state, $\hat{x}(k|k-1)$, and measurement, $z(k)$.

*Proof*: We assume that weighting matrices, $W_{x1}(k)$ and $W_z(k)$, are the inverse covariance matrices associated with state vector and measurement vector, $P^{-1}(k|k-1)$ and $R^{-1}(k)$, respectively. Then weighting matrix of $x_2(k)$ follows from (21), (22), and (23)

$$W_{x2} = H^T R^{-1}(k) H. \qquad (28)$$

The output of DFM with $x_1(k)$ and $x_2(k)$ as its inputs can be determined by (25) as

$$y(k)=\left\{P^{-1}(k|k-1)+H^TR^{-1}(k)H\right\}^{-1} \times\left\{P^{-1}(k|k-1)x_1(k)+H^TR^{-1}Hx_2(k)\right\}. \quad (29)$$

From the matrix inversion lemma [13], it can be shown that

$$\begin{aligned} y(k)=&\left\{P^{-1}(k|k-1)+H^TR^{-1}(k)H\right\}^{-1} \\ &\times P^{-1}(k|k-1)x_1(k) \\ &+\left\{P^{-1}(k|k-1)+H^TR^{-1}(k)H\right\}^{-1} \\ &\times H^TR^{-1}(k)Hx_2(k) \\ =&I-P(k|k-1)H^T \\ &\times\left\{HP(k|k-1)H^T+R(k)\right\}^{-1}Hx_1(k) \\ &+P(k|k-1)H^T \\ &\times\left\{HP(k|k-1)H^T+R(k)\right\}^{-1}Hx_2(k) \\ =&\left\{I-G'(k)H\right\}x_1(k)+G'(k)Hx_2(k) \quad (30) \end{aligned}$$

where

$$\begin{aligned} G'(k)=&P(k|k-1)H^T \\ &\times\left\{HP(k|k-1)H^T+R(k)\right\}^{-1}. \quad (31) \end{aligned}$$

Substituting $x(k|k-1)$ and $H^T(k)z(k)$ in $x_1(k)$ and $x_2(k)$, respectively, give

$$y(k)=\hat{x}(k|k-1)+G'(k)\left\{z(k)-H\hat{x}(k|k-1)\right\}. \quad (32)$$

The derived (32) is the same as the measurement update equation of Kalman filter and $G'(k)$ is the same as Kalman gain matrix. Therefore the proof is done. □

By Theorem 1, Error monitoring and recovery technique of perception net can be applied to detect the error of input data of Kalman filtering. Therefore the inconsistency between the predicted state and measurement in (7) can be detected by checking whether there is a common intersection between the uncertainty ellipsoids of predicted state and measurement. If the inconsistency are detected, the result are used for decision of target maneuvering.

The detecting inconsistency can be performed at every subfilters in step 2 of IMM algorithm. Then the inconsistency detection is performed through the test (for simplicity, we define that $x(k)$ indicates $\hat{x}(k|k-1)$ whenever it is used as a subscript).

$$\|\hat{x}_t(k|k)-\hat{x}_t(k|k-1)\|^2_{W_{xt(k)}}\leq 1 \quad (33)$$

or

$$\left\|\hat{x}_t(k|k)-H^Tz(k)\right\|^2_{W_{H^Tz(k)}}\leq 1, \quad t=1,2,\cdots,N. \quad (34)$$

If the inconsistencies are detected in DFM of subfilter, it means that predicted state or measurement has an error. Fig. 2 shows the results of the inconsistency detection about the conventional IMM filter with 3 models [7] by 100 Monte-Carlo simulations, when target starts to maneuver at 30 *sec* and finishes maneuvering at 55 *sec*. Fig. 2(a) presentes the inconsistencies of subfilter with constant velocity model. Fig. 2(b) and Fig. 2(c) represent the inconsistencies of subfilter with incremental acceleration model and constant acceleration model, respectively. We can find that the inconsistencies appear outstandingly when maneuver starts and finishes.

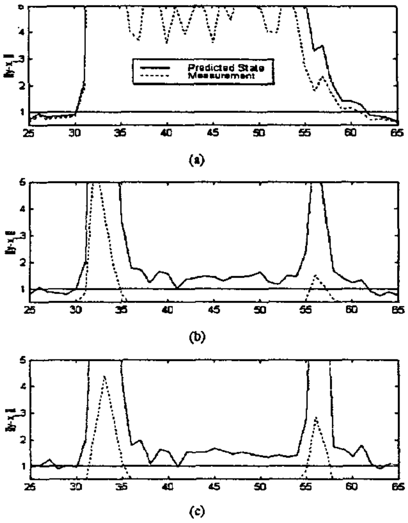


Fig. 2. Inconsistencies between input data in the subfilters: (a)constant velocity model(DFM1), (b)incremental acceleration model(DFM2), (c)constant acceleration model(DFM3)

One cycle of IMM filter with 3 models is depicted in Fig. 3 as net hierarchy by the perception net. Excepting the element marked as "♣", Fig. 3 is the same as the step 2 and the step 3 of IMM filter. DFM 1-3 correspond to the step 2 which means Kalman filtering at subfilters and DFM 4 corresponds to the step 3. When DFM 1-3 detect the inconsistencies between their inputs in every module, DFM 1-3 are marked as "Δ" to indicate that they are in possibly-in-error.

For the isolation of error source, we need to know which input data has an error. When the inconsistencies are detected in every DFM module, we can consider that the predicted states in all model have errors or that the measurement has an error. Each predicted state is dependent on the model probabilities in the previous time as shown in (3) and (6), and is calculated by mixing of estimates. Therefore, although the target maneuver occurs, the predicted state of constant acceleration model is not immediately reflected on estimation of the track. For this reason, the inconsistencies are detected in fusion module for somewhat interval after target has maneuvered. Finally, if there is not an incessant bias in measurement, the inconsistencies of DFM come from the error which the predicted states have. Hence, all predicted states are classified into likely-in-error and are marked as "×". Also the measurement is classified into unlikely-in-error and is marked as "◯".

With the predicted states, the maneuver detection is performed over DFM1, DFM2, and DFM3 through the test

$$\sum_{i=k-g+1}^{k}\sum_{t=1}^{N}U\left\{\|\hat{x}_t(i|i)-\hat{x}_t(i|i-1)\|^2_{W_{xt(i)}}-1\right\}=gN, \quad (35)$$

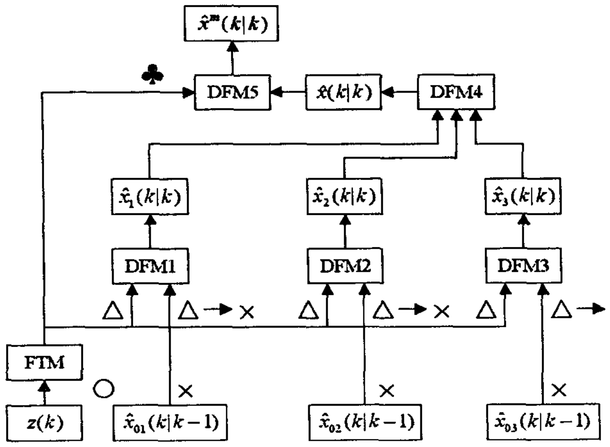


Fig. 3. Perception net representation of IMM filter with 3 models

where $U\{\cdot\}$ is an unit step function, $g$ is the length of a fixed-size window.

The classifications of input data are propagated through the net. Then, the sensor with an error is classified into a defective sensor. the logical sensors which generates the predicted states are classified into a defective sensor and the physical sensor which acquires the measurement is classified into a indefectible sensor. Therefore it is desirable to put an weight on the data(measurement) supplied by the indefectible sensor(physical sensor) for more favorable filtering. If the target maneuver is detected, the final state is updated by fusing its current state with the measurement from FTM, as marked by "♣" in Fig. 3. In order to fuse two data, Kalman filter measurement updata is carried out as follows

$$\hat{x}^m(k|k) = \hat{x}(k|k) + G^m(k)\{z(k) - H\hat{x}(k|k)\}, \quad (35)$$

$$P^m(k|k) = \{I - G^m(k)H\}P(k|k), \quad (36)$$

$$G^m(k) = P(k|k)H^T\left\{HP(k|k)H^T + R(k)\right\} \quad (37)$$

where superscript $m$ denotes the estimation value of time at which maneuver is detected.

In spite of mistake of maneuver decision, the above mensioned method hardly effect on the tracking performance. But the proposed method has an effect on the progress of tracking performance at starting and stopping maneuver. In conclusion, IMM filter which employing the proposed method takes advantage of IMM filter and reduces maximum value of estimation error.

## 5. Simulations

The performance of the proposed error monitoring method is compared with the standard IMM estimator using Monte-Carlo simulations. A target that turns in the two-dimensional space is considered [5]. The target is on a constant course and speed until 30 *sec* and starts to maneuver at 30 *sec* and stops maneuvering at 55 *sec*. Two maneuver input scenarios are considered for performance analysis. When $u_x$ and $u_y$ indicate the maneuver input of $x$ direction and $y$ direction in two-dimensional space, respectively, each scenario of maneuver input acceleration is made up of the maneuver level as follows

Simulation 1: $u_x = -40m/s^2$, $u_y = 40m/s^2$
Simulation 2: $u_x = -60m/s^2$, $u_y = 60m/s^2$.

Sampling time $T = 1\,sec$, the process noise covariance the measurement noise covariance $R_{11} = R_{22} = 144m^2$ and $R_{12} = R_{21} = 5m^2$ are used in the simulation. The real initial state and filter initial state of target are given by

$$x(0) = \begin{bmatrix} 200 & 100 & 0 & 200 & -300 & 0 \end{bmatrix}^T$$
$$\hat{x}(0) = \begin{bmatrix} 190 & 90 & 1 & 190 & -310 & 1 \end{bmatrix}^T.$$

The value of the effective window length is taken to be 2. The IMM filter to be considered is a three-model IMM filter. The first model, $M_1$, is a second-order kinematic model with white noise acceleration. The second model, $M_2$, and the third model, $M_3$, are third-order kinematic models with white noise acceleration increments with different variances. Model $M_2$ has process noise with a standard deviation of $10m/s^2$ and model $M_3$ has process noise with a standard deviation of $4m/s^2$. The assumed model switching probabilities (Markov chain transition probabilities) are indicated in Table 1.

Table 1. Model switching propabilities

| | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|
| $M_1$ | 0.85 | 0.15 | 0 |
| $M_2$ | 0.33 | 0.34 | 0.33 |
| $M_3$ | 0 | 0.15 | 0.85 |

100 Monte-Carlo simulations were performed. Fig. 4 gives position RMS errors for both the conventional IMM and error monitoring IMM, while Fig. 5 gives the corresponding velocity RMS errors.

It is seen from Fig. 4 that the RMS error in the proposed filter is nearly equal to those in the conventional IMM filter before a maneuver start. Since the target maneuvers, the conventional IMM filter is slowly adapt to maneuvering mode until the constant acceleration model has enough model probability to play a main role in estimating the track. On the other hand, the proposed filter detects a target maneuver and the RMS errors decrease quickly more than that of conventional IMM.

The RMS error in stopping maneuvering is similar to that in beginning maneuvering. There is only slice difference between two filter in case of the RMS errors of velocity. In simulation 2, the target that turns rapidly was considered. Fig. 6 is the plot of the conventional IMM filter and proposed filter. In this case, Fig. 6 shows that the peak error of the proposed filter is outstandingly reduced while the target maneuver.

Overall, the proposed filter is adaptable to highly maneuvering input level and repeated maneuvering case. Furthermore, the algorithm of proposed filter is very simple and is not harmful to advantage of conventional IMM.

## 6. Conclusions

In this paper, the modified IMM scheme is derived by adding the error monitoring and recovery technique to conventional IMM filter. To do this, it is also proved that the geometric data fusion method of perception net has the same decription as the measurement update of Kalman filter. The maneuvering is detected by the proposed error monitoring and recovery technique based on perception net. If the maneuvering is detected, then the estimated state of conventional IMM filter is combined with the measurement in order to put weight on the measurement. Its effectiveness has been demonstrated through simulations. The proposed method shows higher performance for a highly maneuvering target as well as it reduces maximum values of estimation errors when maneuvering starts and finishes.

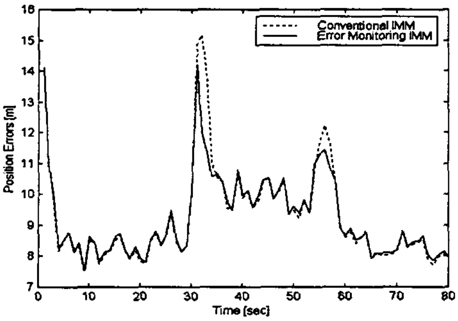


Fig. 4. Position RMS errors of proposed filter and conventional IMM filter (simulation 1)

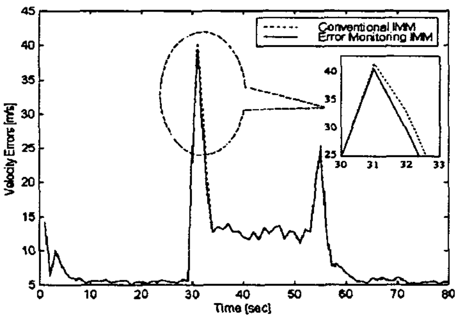


Fig. 5. Velocity RMS errors of proposed filter and conventional IMM filter (simulation 1)

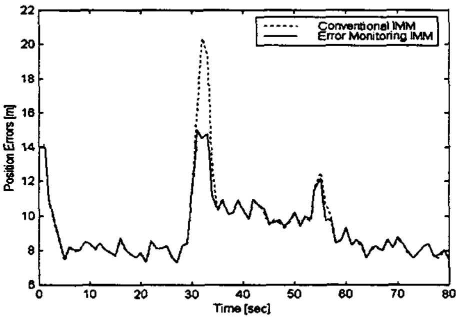


Fig. 6. Position RMS errors of proposed filter and conventional IMM filter (simulation 2)

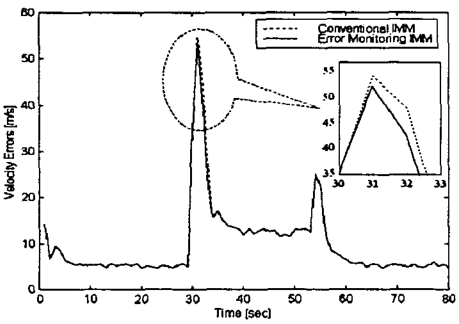


Fig. 7. Velocity RMS errors of proposed filter and conventional IMM filter (simulation 2)

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