Design of Adaptive Fuzzy IMM Algorithm for Tracking the Maneuvering Target with Time-varying Measurement Noise

Hyun-Sik Kim and In-Ho Kim

Abstract: In real system application, the interacting multiple model (IMM) based algorithm operates with the following problems: it requires less computing resources as well as a good performance with respect to the various target maneuvering, it requires a robust performance with respect to the time-varying measurement noise, and further, it requires an easy design procedure in terms of its structures and parameters. To solve these problems, an adaptive fuzzy interacting multiple model (AFIMM) algorithm, which is based on the basis sub-models defined by considering the maneuvering property and the time-varying mode transition probabilities designed by using the mode probabilities as the inputs of the fuzzy decision maker whose widths are adjusted, is proposed. To verify the performance of the proposed algorithm, a radar target tracking is performed. Simulation results show that the proposed AFIMM algorithm solves all problems in the real system application of the IMM based algorithm.

Keywords: Adaptive fuzzy interacting multiple model algorithm, basis sub-models, maneuvering target tracking, time-varying mode transition probabilities.

1. INTRODUCTION

The Kalman filter, which is well known as a recursive estimator based on optimal filter theory, has been widely used in target tracking. However, in the case that a single filter is used in the maneuvering target tracking, its performance worsens. For this reason, many kinds of tracking algorithms using the Kalman filter have been studied in order to solve this problem. Among them, the interacting multiple model (IMM) algorithm is well known to have a good performance even though it is a sub-optimal filter [1-4]. In the IMM based algorithm, if the target maneuvering is similar to the output of a sub-model, the tracking error is small; otherwise, the error is big. For this reason, it requires many sub-models in order to have a good performance with respect to the various target maneuvering. Nevertheless, it is unreasonable to use the algorithm that has more computing resources in the real system application. Also, the performance of the IMM based algorithm depends on the mode transition probabilities as well as the sub-models, i.e., if the mode transition probabilities are adjusted, the performance of the IMM based algorithm is better than that of the conventional IMM based algorithm. Moreover, the performance of the IMM based algorithm depends on the measurement noise, i.e., if the measurement noise is increased in the case that a sub-model matches with the target maneuvering, its performance worsens because the values of the mode probabilities which generate the combined state become similar.

To solve these problems, various IMM based algorithms have been suggested. Lee [5] proposed the algorithm that has three optimal sub-models whose parameters are adjusted by the genetic algorithm (GA). Although it has a small number of sub-models as well as a good performance, it still has a computational burden in optimizing sub-models by the GA. Campo [6] proposed the algorithm that adjusts the mode transition probabilities by the sojourn time dependent Markov model switching. Although it has better performance, it has difficulty in determining the design parameters. Kim [7] proposed the fuzzy interacting multiple model (FIMM) algorithm that utilizes the basis sub-models defined by considering the maneuvering property and adjusts the mode transition probabilities designed by using the mode probabilities as the inputs of a fuzzy decision maker. Although it has an easy design procedure as well as less computing resources and a good performance, it still depends on the measurement noise.

To resolve these problems, an adaptive fuzzy interacting multiple model (AFIMM) algorithm, which is based on the basis sub-models defined by considering the maneuvering property and the time-varying mode transition probabilities designed by

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Hyun-Sik Kim and In-Ho Kim are with the Department of Robot System Engineering, Tongmyong University, 535, Yongdang-dong, Nam-gu, Busan, 608-711, Korea (e-mails: {hyunskim, ihkim}@tu.ac.kr).

using the mode probabilities as the inputs of the fuzzy decision maker whose widths are adjusted, is proposed.

The design procedure of the AFIMM algorithm encompasses the following contents: the practical definition method of the basis sub-models defined by considering the maneuvering property; and the easy design method of the time-varying mode transition probabilities designed by using the mode probabilities as the inputs of the fuzzy decision maker whose widths are adjusted.

The proposed algorithm has four major advantages: 1) it has less computing resources because the number of basis sub-models is small 2) it has more robust performance with respect to the various target maneuvering and the time-varying measurement noise because the mode transition probabilities are adjusted by the fuzzy decision maker whose widths are adjusted 3) it has an easy fuzzy partition and an easy fuzzy rule because the mode probabilities are normalized values and the sum of them is 1.0, and 4) it easily extends the simplified fuzzy reasoning method [8,9] because the mode transition probabilities have the form of a matrix.

The IMM algorithm is introduced in Section 2. The design of the proposed AFIMM algorithm is described in Section 3, and the simulation results of the proposed AFIMM algorithm with respect to the various target maneuvering are presented in Section 4. Finally, the conclusions are summarized in Section 5.

2. IMM ALGORITHM

In this section, the main elements of the IMM algorithm, which is based on the Kalman filter, are introduced.

The IMM algorithm is well known to have good performance with respect to the various target maneuvering although it is a sub-optimal filter based on the Markov chain whose transition depends on the latest state. The detail contents are well explained in [3], and the main elements of the IMM algorithm are as follows:

The mode transition probabilities, which are related to Markov chain, are defined as

$$\boldsymbol{p}_{ij} = P\{M_j(k)|M_i(k-1)\} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1j} \\ p_{21} & p_{22} & \cdots & p_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ p_{i1} & p_{i2} & \cdots & p_{ij} \end{bmatrix}, \quad (1)$$

where $i,\ j = 1,2,\ldots,r$ and r is the number of sub-models.

And the mixing probability is defined as

$$\mu_{ij}(k-1|k-1) = \frac{1}{c_j} p_{ij}\mu_i(k-1), \quad (2)$$

where c_j is the normalization constant of j-th sub-model, and $\mu_i(k-1)$ denotes i-th mode probability at the scan $k-1$.

$$c_j = \sum_{i=1}^{r} p_{ij}\mu_i(k-1). \quad (3)$$

And then, the mixed state and the state covariance are defined as

$$\hat{\boldsymbol{x}}_0^j(k-1|k-1) = \sum_{i=1}^{r} \hat{\boldsymbol{x}}^i(k-1|k-1)\mu_{ij}(k-1|k-1), \quad (4)$$

$$\begin{aligned} \boldsymbol{P}_0^j(k-1|k-1) = \sum_{i=1}^{r} \mu_{ij}(k-1|k-1)\Big\{ & \boldsymbol{P}^i(k-1|k-1) \\ & + \left[\hat{\boldsymbol{x}}^i(k-1|k-1) - \hat{\boldsymbol{x}}_0^i(k-1|k-1)\right] \\ & \left[\hat{\boldsymbol{x}}^i(k-1|k-1) - \hat{\boldsymbol{x}}_0^i(k-1|k-1)\right]^T \Big\}, \end{aligned} \quad (5)$$

where $\hat{\boldsymbol{x}}^i(k-1|k-1)$ is the state vector.

Also, the mode probability is defined as

$$\mu_j(k) = \frac{1}{c}\Lambda_j(k)c_j, \quad (6)$$

where c is a normalization constant.

$$c = \sum_{j=1}^{r} \Lambda_j(k)c_j, \quad (7)$$

and $\Lambda_j(k)$ is a likelihood function defined as

$$\Lambda_j(k) = \frac{1}{\sqrt{(2\pi)^{n_z}|S_j(k)|}} \exp\left(-\frac{1}{2}\nu_j^T(k)S_j^{-1}(k)\nu_j(k)\right), \quad (8)$$

and $\nu_j(k) = z(k) - \hat{z}_j(k-1|k)$, $S_j(k)$ is the innovation covariance that includes the measurement covariance, and n_z is the dimension of measurement vector $z(k)$.

Finally, the combined state and the state covariance are defined as

$$\hat{\boldsymbol{x}}(k|k) = \sum_{j=1}^{r} \hat{\boldsymbol{x}}^j(k|k)\mu_j(k), \quad (9)$$

$$\begin{aligned} \boldsymbol{P}(k|k) = \sum_{j=1}^{r} \mu_j(k)\Big\{ & \boldsymbol{P}^j(k|k) + \left[\hat{\boldsymbol{x}}^j(k|k) - \boldsymbol{x}(k|k)\right] \\ & \left[\hat{\boldsymbol{x}}^j(k|k) - \hat{\boldsymbol{x}}(k|k)\right]^T \Big\}, \end{aligned} \quad (10)$$

From the above mentioned (1)-(10), we note that the performance of the IMM algorithm depends on the mode transition probabilities as well as the sub-models, i.e., if the target maneuvering is similar to the output of a sub-model, the tracking error is small; otherwise, the error is relatively big; and if the values of a column in (1) are increased, the corresponding sub-model is strongly reflected in generating the combined state in (9); if the values of all columns are equally assigned, all sub-models are equally reflected.

3. DESIGN OF AFIMM ALGORITHM

In this section, an AFIMM algorithm, which is based on the basis sub-models defined by considering the maneuvering property and the time-varying mode transition probabilities designed by using the mode probabilities as the inputs of the fuzzy decision maker whose widths are adjusted, is designed.

The one cycle AFIMM algorithm that has the fuzzy decision maker, which includes a width decisioner, a normalizer, a dominant signal generator, and an arc signal generator, is shown in Fig. 1.

The detail design procedure of the AFIMM algorithm is divided into the following two phases:

In the first phase of the design procedure, the practical definition method of the basis sub-models, which is defined by considering the maneuvering property, is described as follows:

Generally, the maneuvering property can be expressed by

$$Maneuvering\ Property = f(v, a, \omega, T, \sigma_w), \quad (11)$$

where v is target speed, a is target acceleration, ω is target angular velocity, T is sampling period, and σ_w is the standard deviation of the measurement noise.

The kinematic models can be divided into four types: a constant velocity (CV) model, a Singer (SG) model [4], a constant acceleration (CA) model, and a coordinated turn (CT) model.

However, if the maneuvering property and the kinematic models are considered in the definition of sub-models by the designer, the definition is executed by the method that is shown in Fig. 2.

This method explains that the maneuvering property is closely related to the elements such as target speed, target acceleration, target angular velocity, sampling period, and the standard deviation of the measurement noise, i.e., if the sampling period is small or the standard deviation of the measurement noise is large, the number of sub-models can be reduced because unnecessary sub-models can exist.

According to the analysis of the above mentioned definition method, the kinematic models can be interpreted as the acceleration models that have different acceleration rates and axis-coupling rates as follows:

$$CV < SG \le CA << CT, \quad (12)$$

This relation implies that SG and CA models can be

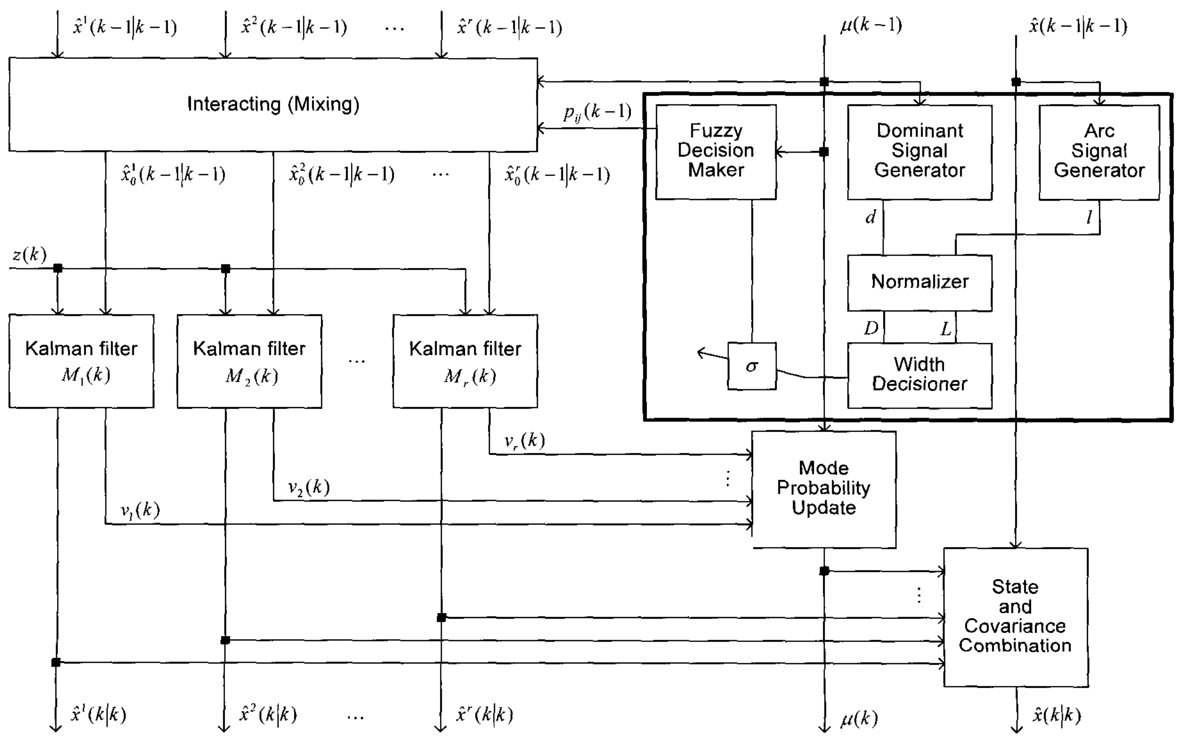

Fig. 1. AFIMM algorithm (one cycle).

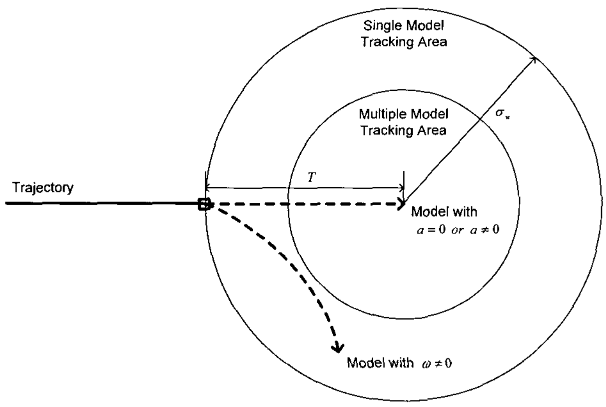

Fig. 2. Sub-model definition method.

unnecessary sub-models because they can be made by the weighted sum of the CV and CT models that can be candidates for basis sub-models. And the ω of the CT model can be determined because the maximum turning rate of the desired target is generally known although its turning direction is unknown.

Therefore, in the horizontal plane, two basis sub-models composed of CV model and CA model can be sufficient for general tracking of the vertical maneuvering target and three basis sub-models composed of one CV model and two CT models can be sufficient for general tracking of the horizontal maneuvering target.

Consequently, the number of basis sub-models is small. Note that it solves the problem of less computing resources in the real system application of the IMM based algorithm.

In the second phase of the design procedure, the easy design method of the time-varying mode transition probabilities, which is designed by using the mode probability as the inputs of the fuzzy decision maker whose widths are adjusted, is described as follows:

To adjust the mode transition probabilities in (1), the performance index is needed for evaluating each sub-model. Incidentally, the mode probability in (6) plays a role in evaluating each sub-model because the mode probability is the function of the likelihood function that includes the innovation covariance in (8). Therefore, the mode probabilities are used as the fuzzy inputs.

The fuzzy partition for the fuzzy decision maker employs five bell-shaped membership functions that are shown in Fig. 3.

This partition has the membership function that is defined as

$$f_{A_i^n}(\mu_i(k-1)) = \exp\left[-\left(\frac{\mu_i(k-1)-c_i^n}{\sigma_n}\right)^2\right], \quad (13)$$

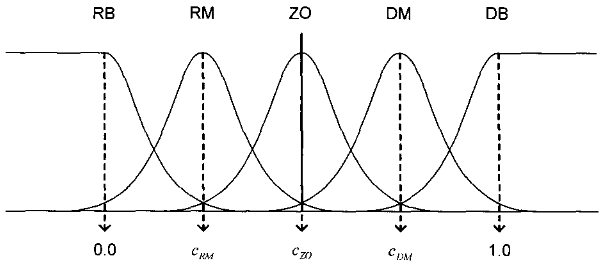

Fig. 3. Fuzzy partition for AFIMM.

where $n = 0,1,2,\ldots,r$ is fuzzy rule number, A_i^n is linguistic term, c_i^n and σ_n are respectively the center and the width of n-th fuzzy rule.

And it is based on the facts that the mode probabilities in (6) are normalized values and the sum of them is 1.0. This is directly related to use the mode probabilities as fuzzy inputs. From these facts, the centers of DB and RB membership functions are respectively set to 1.0 and 0.0, and the center of ZO membership function is easily set to

$$c_{ZO} = 1/r. \quad (14)$$

And the center of the DM membership function is properly set by considering the degree of similarity between sub-models, i.e., if the degree of similarity between sub-models is high, c_{DM} is close to c_{ZO}; otherwise, it is far from c_{ZO}. Then, the center of RM membership functions is set by the above mentioned facts:

$$c_{RM} = (1-c_{DM})/(r-1). \quad (15)$$

However, the widths are practical parameters because they are easily ranged and the output of the fuzzy decision maker is sensitive to their values, i.e., if they are adjusted easily, the performance of the fuzzy decision maker can be improved. Here, the time-varying widths are equally set for the design simplicity:

$$\sigma_n = \sigma. \quad (16)$$

In the design of the fuzzy adaptation rule for deciding of σ, the dominant signal d and the arc signal l are defined as

$$d = \max(\mu_i(k-1)) - c_{ZO},$$
$$l = \hat{R}(k-1)\theta_{BW} - R_{\min}\theta_{BW}, \quad (17)$$

where $\hat{R}(k-1)$ is the estimated range which is calculated from (9). θ_{BW} and $R_{\min}$ are respectively the beam width and minimum range of the sensor system. The signals are easily normalized by $1-c_{ZO}$

and $R_{\max}\theta_{BW} - R_{\min}\theta_{BW}$ because the mode probability is normalized values and $R_{\min}$ and the maximum range $R_{\max}$ are generally known in the sensor system. Here, the range error and beam width error are ignored.

The fuzzy reasoning method for the fuzzy decision maker employs the simplified method whose consequent part has a constant value, i.e., the fuzzy rule for deciding the mode transition probabilities in (1) easily extends a constant value to a matrix because the mode transition probabilities have the form of a matrix; and the fuzzy adaptation rule for deciding the width σ in (16) is directly utilized because the width has a constant value.

The fuzzy rule is based on the idea of deciding the mode transition probabilities in (1) according to the existence of the dominant model. The related rule has the following form:

$$R^n: \text{if } \mu_1 \text{ is } A_1^n \text{ and } \mu_2 \text{ is } A_2^n \text{ and} \cdots \text{and } \mu_r \text{ is } A_r^n \text{ then } \boldsymbol{p}_{ij} = \boldsymbol{p}_{ij}^n, \tag{18}$$

where R^n denotes the n-th fuzzy rule, and $\boldsymbol{p}_{ij}^n$ that comprises the consequent part is expressed by

$$\boldsymbol{p}_{ij}^n = \begin{bmatrix} p_1 & p_2 & \cdots & p_j \\ p_1 & p_2 & \cdots & p_j \\ \vdots & \vdots & \ddots & \vdots \\ p_1 & p_2 & \cdots & p_j \end{bmatrix}, \tag{19}$$

where

$$p_j = \begin{cases} 1/r, & n = 0 \\ p_{\max}, & n \neq 0 \text{ and } j = n, \\ (1 - p_{\max})/(r-1), & n \neq 0 \text{ and } j \neq n \end{cases} \tag{20}$$

and (21) shows the proposed fuzzy rule

$$\begin{aligned} R^0 &: \text{if } \mu_1 \text{ is } ZO \text{ and } \mu_2 \text{ is } ZO \text{ and} \ldots \text{and } \mu_r \text{ is } ZO \text{ then } \boldsymbol{p}_{ij} = \boldsymbol{p}_{ij}^0 \\ R^1 &: \text{if } \mu_1 \text{ is bigger than } DM \text{ and } \mu_2 \text{ is smaller than } RM \text{ and} \ldots \text{and } \mu_r \text{ is smaller than } RM \text{ then } \boldsymbol{p}_{ij} = \boldsymbol{p}_{ij}^1 \\ R^2 &: \text{if } \mu_2 \text{ is bigger than } DM \text{ and } \mu_3 \text{ is smaller than } RM \text{ and} \ldots \text{and } \mu_1 \text{ is smaller than } RM \text{ then } \boldsymbol{p}_{ij} = \boldsymbol{p}_{ij}^2 \\ &\vdots \\ R^r &: \text{if } \mu_r \text{ is bigger than } DM \text{ and } \mu_1 \text{ is smaller than } RM \text{ and} \ldots \text{and } \mu_{r-1} \text{ is smaller than } RM \text{ then } \boldsymbol{p}_{ij} = \boldsymbol{p}_{ij}^r. \end{aligned} \tag{21}$$

Table 1. Proposed fuzzy adaptation rule.

D \ L	S	M	B
DS	0.9	0.8	0.7
DM	0.6	0.5	0.4
DB	0.3	0.2	0.1

The equation has only $r+1$ rules and includes the following rules: if the dominant model exists, the values of the corresponding column in (1) are increased in order to strongly reflect the corresponding sub-model in generating the combined state in (9); otherwise, the values of all columns are equally assigned in order to equally reflect all sub-models. It enables that the adjusted mode transition probabilities are expressed by the form of the weighted sum of the consequent parts.

The fuzzy adaptation rule is based on the idea of deciding the width σ in (16) according to d and l in (17). The related rule has the following form:

$$R^m: \text{if } D \text{ is } B_1^m \text{ and } L \text{ is } B_2^m \text{ then } \sigma = \sigma^m, \tag{22}$$

where $R^m (m = 1,2,\ldots,9)$ denotes the m-th fuzzy adaptation rule, D and L are respectively the normalized values of d and l, B_1^m and B_2^m are linguistic terms, and σ^m is the consequent part. The widths for D and L are set to σ_2 and σ_3 respectively and Table 1 shows the proposed fuzzy adaptation rule.

The table has only nine rules and includes the following rules: if D or L are increased in the cases that a dominant model is growing or the measurement noise is increasing, the width should be decreased in order to decrease the mixing rate of basis sub-models or compensate the range effect in (8); otherwise, the width should be increased. The outputs use the value that has a same difference satisfying a normal fuzzy partition condition of $0 < \sigma < 1$, which is related to Fig. 3. It enables that the fuzzy decision maker has a more optimal parameter.

The fuzzy defuzzification related to the fuzzy rule is expressed by the following form:

$$\boldsymbol{p}_{ij}(k) = \frac{\sum_{n=0}^{r} w_n \boldsymbol{p}_{ij}^n}{\sum_{n=0}^{r} w_n}, \tag{23}$$

where

$$w_n = \prod_{i=1}^{r} f_{A_i^n}(\mu_i(k-1)). \tag{24}$$

This fuzzy decision maker replaces the time-invariant p_{ij} in (1)–(3) to the time-varying $p_{ij}(k)$ in (23). It enables to let the AFIMM algorithm have better performance than that of the conventional IMM based algorithm.

Consequently, the fuzzy decision maker has a simply composed structure and easily determined parameters as well as more robust performance. Note that they solve the problems of both more robust performance and an easy design procedure in the real system application of the IMM based algorithm.

From the above mentioned procedure, the AFIMM algorithm, which is based on the basis sub-models defined by considering the maneuvering property and the time-varying mode transition probabilities designed by using the mode probabilities as the inputs of the fuzzy decision maker whose widths are adjusted, has been designed.

4. SIMULATION RESULTS

The performance of the AFIMM algorithm is tested with the problem of tracking a radar target moving, which is described by the constant velocity flight and the coordinated turn flight in the horizontal plane. It was also shown in [7,10].

The process equations, which are related to the constant velocity flight and the coordinated turn flight of the radar target, are defined as

$$\boldsymbol{x}(k+1) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \boldsymbol{x}(k) + \begin{bmatrix} T^2/2 \\ T \\ T^2/2 \\ T \end{bmatrix} v(k), \tag{25}$$

$$\boldsymbol{x}(k+1) = \begin{bmatrix} 1 & \sin\omega T/\omega & 0 & -(1-\cos\omega T)/\omega \\ 0 & \cos\omega T & 0 & -\sin\omega T \\ 0 & (1-\cos\omega T)/\omega & 1 & \sin\omega T/\omega \\ 0 & \sin\omega T & 0 & \cos\omega T \end{bmatrix} \boldsymbol{x}(k) + \begin{bmatrix} T^2/2 \\ T \\ T^2/2 \\ T \end{bmatrix} v(k). \tag{26}$$

The state vector is defined as

$$\boldsymbol{x}(k) = \begin{bmatrix} \xi & \dot{\xi} & \eta & \dot{\eta} \end{bmatrix}^T, \tag{27}$$

where ξ, $\dot{\xi}$ are respectively the position and velocity of target with respect to x-axis, and η, $\dot{\eta}$ are respectively the position and velocity of target with respect to y-axis in Cartesian coordinates.

The measurement equation is defined as

$$z(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \boldsymbol{x}(k) + w(k). \tag{28}$$

The simulation scenario of the maneuvering target is designed as follows:

A nonmaneuvering flight during scan 1 to 20 with a speed of 300m/s; a 180° turning flight during scan 21 to 33 with a turning rate of $3.74^\circ/\text{s}$ (2g acceleration); a nonmaneuvering flight during scan 34 to 53; a -180° turning flight during scan 54 to 66 with a turning rate of $-3.74^\circ/\text{s}$; a nonmaneuvering flight during scan 67 to 86; a 180° turning flight during scan 87 to 112 with a turning rate of $1.87^\circ/\text{s}$; finally, a nonmaneuvering flight during scan 113 to 132.

In order to compare the proposed AFIMM algorithm with conventional IMM based algorithms, an IMM1 with no knowledge, an IMM2 with a heuristic knowledge and a FIMM [7] are considered. The initial state of target in Cartesian coordinates is determined by

$$\boldsymbol{x}(0) = \begin{bmatrix} 30000 & -172 & 30000 & -246 \end{bmatrix}^T.$$

The process noise of a true system is zero and the true trajectory is shown in Fig. 4.

The sampling period of a sensor system is determined by $T = 3.5$. The standard deviation of measurement noise and the beam width in the sensor system are determined by $R\theta_{BW}$ and $\theta_{BW} = 0.1^\circ$ respectively. Here, R is the range.

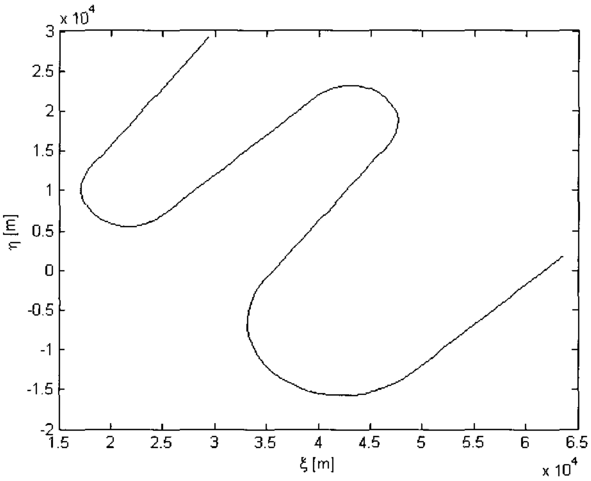

Fig. 4. True trajectory of maneuvering target.

Table 2. Parameters of algorithms.

	IMM1	IMM2	FIMM	AFIMM
IMM's	$p_{ij} = \begin{bmatrix} 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \end{bmatrix}$	$p_{ij} = \begin{bmatrix} 0.95 & 0.05 & 0.05 \\ 0.025 & 0.70 & 0.25 \\ 0.025 & 0.25 & 0.70 \end{bmatrix}$	$p_{ij}(0) = \begin{bmatrix} 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \end{bmatrix}$	$p_{ij}(0) = \begin{bmatrix} 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0.33 \end{bmatrix}$
Fuzzy's	-	-	$c_{DM} = 0.66, \quad \sigma = 0.33$ $p_{\max} = 0.98$	$c_{DM} = 0.66$ $p_{\max} = 0.98$
Adaptive Fuzzy's	-	-	-	$\begin{bmatrix} c_{DS} = 0.0 & c_{DM} = 0.5 & c_{DB} = 1.0 \end{bmatrix}$ $\begin{bmatrix} c_S = 0.0 & c_M = 0.5 & c_B = 1.0 \end{bmatrix}$ $\sigma_2 = 0.5, \quad \sigma_3 = 0.5$

In order to track the maneuvering target, the number of basis sub-models is $r = 3$, which is determined by

$$M = \left[\omega_1 = 0, \quad \omega_2 = 2g, \quad \omega_3 = -2g\right]^T.$$

The noise covariance is

$$Q = \begin{bmatrix} T^4/4 & T^3/2 & 0 & 0 \\ T^3/2 & T^2/2 & 0 & 0 \\ 0 & 0 & T^4/4 & T^3/2 \\ 0 & 0 & T^3/2 & T^2/2 \end{bmatrix} \sigma_v^2, \tag{29}$$

where $\sigma_v = 0.004$.

The standard deviation of measurement noise in the filter is determined by $\hat{R}\theta_{BW}$.

The above parameters are equally applied to all algorithms. The other parameters are given in Table 2.

The performance of the AFIMM is tested by 100 times Monte Carlo simulation. The results are shown in Figs. 5-11. These are RMSE or RMS values.

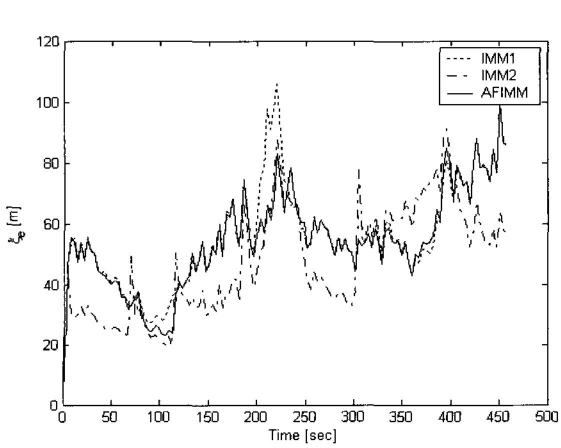

Fig. 5. RMSE of target position (ξ -axis).

Figs. 5 and 6 respectively show the RMSE of target position and velocity with respect to ξ -axis. And Figs. 7 and 8 respectively show the RMSE of target position and velocity with respect to η -axis. While the performances of all algorithms have the relation of IMM1 < AFIMM < IMM2 in the basis sub-model matched case, they have the relation of IMM2 <

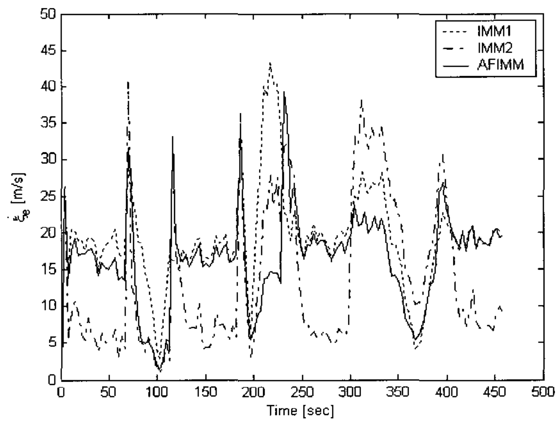

Fig. 6. RMSE of target velocity (ξ -axis).

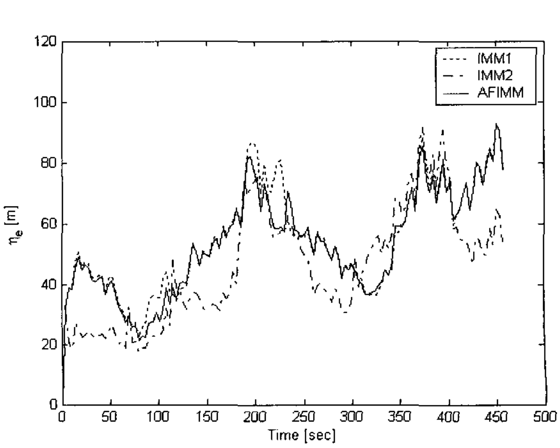

Fig. 7. RMSE of target position (η -axis).

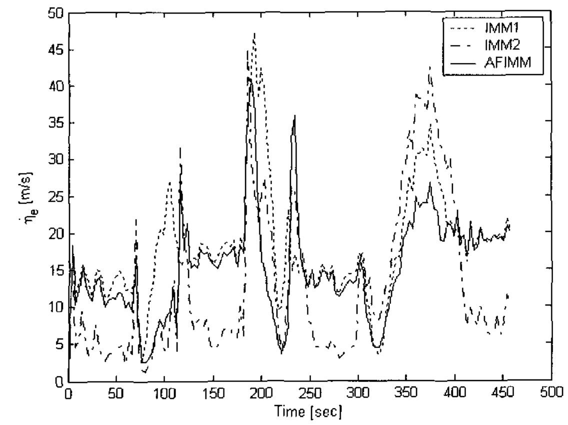

Fig. 8. RMSE of target velocity (η -axis).

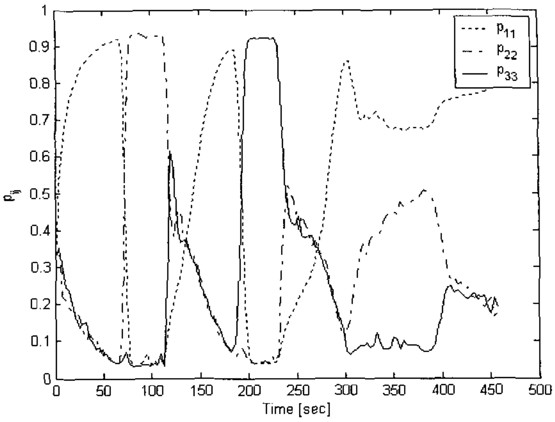

Fig. 9. RMS value of p_{ij} (FIMM).

Table 3. Comparison of performances and CPU time.

	$\lvert\xi_e\rvert_{avg}$	$\lvert\dot{\xi}_e\rvert_{avg}$	$\lvert\eta_e\rvert_{avg}$	$\lvert\dot{\eta}_e\rvert_{avg}$	CPU time [sec]
IMM1	55.090 (53.238)	18.851 (18.254)	54.842 (55.241)	18.473 (19.407)	0.0048
IMM2	53.524 (63.714)	17.473 (24.042)	51.829 (61.967)	17.123 (24.391)	0.0048
FIMM	54.206 (55.005)	16.652 (18.221)	53.793 (55.774)	16.201 (18.668)	0.0064
AFIMM	54.164 (53.436)	16.040 (15.274)	53.882 (55.056)	15.456 (15.866)	0.0066

IMM1 < AFIMM in the mismatched case during scans 87 to 112. These are caused by the facts that the AFIMM has the time-varying probabilities and membership function widths while the IMM1 and IMM2 have the time-invariant mode transition probabilities. These mean that AFIMM is most robust in terms of performances with respect to the overall target maneuvering because the basis sub-model selected from basis sub-model candidates in (12) and the fuzzy decision maker with time-varying mode transition probabilities in (23) act well.

Table 3 shows the numerical comparison of the AFIMM and the conventional IMM based algorithms. $\lvert\xi_e\rvert_{avg}$, $\lvert\dot{\xi}_e\rvert_{avg}$ and $\lvert\eta_e\rvert_{avg}$, $\lvert\dot{\eta}_e\rvert_{avg}$ are the average values of both the average values of RMSE in the mismatched case and the average values of RMSE in the matched case. In parentheses, they are only the average values of RMSE in the mismatched case. These mean that the AFIMM is more effective than the other algorithms in the uncertain target maneuvering. And CPU time is the average value of RMS value. In terms of the performances, the position performances of the AFIMM are better than the other algorithms. Especially, the velocity performances of the AFIMM are superior to the other algorithms. And in terms of one cycle computing resources, the fuzzy decision maker of the AFIMM requires the computing resource equivalent to that of one sub-model in the IMM algorithm. Therefore, the AFIMM and FIMM algorithms require the computing resources of $r+1$ sub-models while the other algorithms may require the computing resources of more than $r+1$ sub-models in order to get the same performances in general. These values quantitatively verify that AFIMM is most effective in terms of both computing resources and performances with respect to the overall target maneuvering.

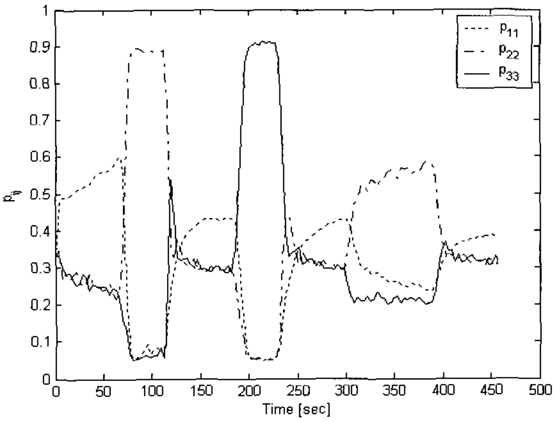

Fig. 10. RMS value of p_{ij} (AFIMM).

Figs. 9 and 10 show the diagonal RMS value of the mode transition probabilities of the FIMM and the AFIMM respectively. The AFIMM is effectively adjusting the mode transition probabilities with respect to the change of the target maneuvering. The AFIMM is correctly distinguishing a dominant sub-model from the sub-models and reflecting the dominant rate of the corresponding sub-model in generating the combined state in all cases in which the dominant sub-model exists, while the FIMM is incorrectly distinguishing a dominant sub-model from the sub-models in the long-range maneuvering case. These mean that the fuzzy decision maker with the

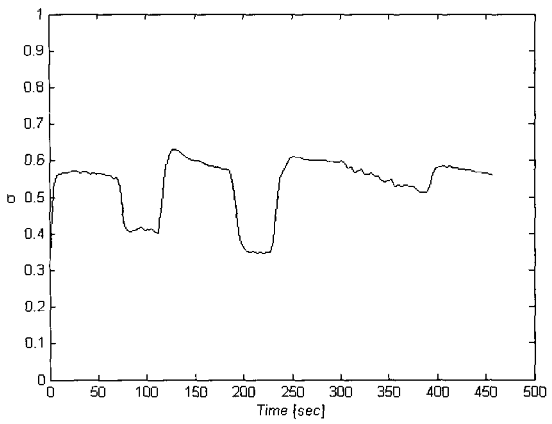

Fig. 11. RMS value of membership function width.

time-varying membership function width from (22) has more optimal parameters than that of the FIMM.

Fig. 11 shows the RMS value of the time-varying membership function width from (22). The AFIMM algorithm is adapting well with respect to the changes of the target maneuvering and measurement noise. The trend of the width is well matching with that of the dominant model in Fig. 10. In the case that the dominant sub-model exists, the width is decreased in order to decrease the mixing rate of basis sub-models or compensate the range effect in (8) whether the basis sub-model is matched or not. This means that the width decisioner using the dominant signal and the arc signal in (17) is valid.

Although the comparisons are not executed under the same conditions with respect to the IMM based algorithms because there does not yet exist the algorithm capable of solving all the problems in the real system application of the IMM based algorithm, they show well that the AFIMM algorithm has meaningful terms.

5. CONCLUSIONS

In this paper, the adaptive fuzzy interacting multiple model algorithm, which is based on the basis sub-models defined by considering the maneuvering property and the time-varying mode transition probabilities designed by using the mode probabilities as the inputs of the fuzzy decision maker whose widths are adjusted, has been proposed.

In the first phase of the design procedure, the practical definition method of the basis sub-models defined by considering the maneuvering property, has been described in order to let the algorithm have less computing resources.

In the second phase of the design procedure, the easy design method of the time-varying mode transition probabilities designed by using the mode probability as the input of the fuzzy decision maker whose widths are adjusted, has been described in order to let the algorithm have both more robust performance and an easy design procedure.

The proposed algorithm has four major advantages: 1) it has less computing resources because the number of basis sub-models is small 2) it has more robust performance with respect to the various target maneuvering and the time-varying measurement noise because the mode transition probabilities are adjusted by the fuzzy decision maker whose widths are adjusted 3) it has an easy fuzzy partition and an easy fuzzy rule because the mode probabilities are normalized values and the sum of them is 1.0, and 4) it easily extends the simplified fuzzy reasoning method because the mode transition probabilities have the form of a matrix.

To verify the performance of the proposed algorithm, radar target tracking has been performed. The simulation results have shown that the proposed AFIMM algorithm effectively solves the problems such as good and robust performance, less computing resources, and easy design procedures in the real system application of the IMM based algorithm. With the Monte Carlo simulation, the results have guaranteed the performances of the AFIMM algorithm.

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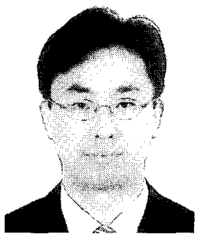
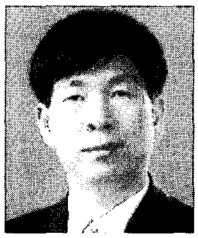


Hyun-Sik Kim received the B.S., M.S., and Ph.D. degrees in Electrical Engineering from Pusan National University, Korea in 1994, 1996, and 2001, respectively. He had been a Senior Researcher at the Agency for Defense Development. He is now an Assistant Professor of Dept. of Robot System Engineering in Tongmyong University. His research interests include intelligent control, evolutionary algorithms, robotics, underwater vehicle control, target tracking, and underwater target classification.



In-Ho Kim received the B.S., M.S., and Ph.D. degrees in Mechanical Engineering from Pusan National University, Korea in 1985, 1988, and 1992, respectively. He is now an Associate Professor of Dept. of Robot System Engineering in Tongmyong University. His research interests include design and manufacturing automation, process control, fuzzy system, and target tracking.