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SIMM Method Based on Acceleration Extraction for Nonlinear Maneuvering Target Tracking

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Abstract – This paper presents the smart interacting multiple model (SIMM) using the concept of predicted point and maximum noise level. Maximum noise level means the largest value of the mere noises. We utilize the positional difference between measured point and predicted point as acceleration. Comparing this acceleration with the maximum noise level, we extract the acceleration to recognize the characteristics of the target. To estimate the acceleration, we propose an optional algorithm utilizing the proposed method and the Kalman filter (KF) selectively. Also, for increasing the effect of estimation, the weight given at each sub-filter of the interacting multiple model (IMM) structure is varying according to the rate of noise scale. All the procedures of the proposed algorithm can be implemented by an on-line system. Finally, an example is provided to show the effectiveness of the proposed algorithm.

Keywords: Acceleration, Kalman Filter (KF), Interacting Multiple Model (IMM), Maneuvering target tracking

1. Introduction

Nowadays, the target tracking problem including target dynamics, maneuvering target tracking, and measurement origin uncertainty has become not only a military interest but also closely linked applications to our lives [1-5]. The Kalman filter (KF) made the tracking problem grow and sustain the capability of that until now. The standard KF is well-known as successfully applicable with nearly constant velocity but unacceptable in case of nonlinear maneuver since the unknown acceleration works as a large process noise on the dynamic model. In order to solve this problem, a variety of techniques have been studied and developed in the field of the state estimation over decades [6-9].

The first attempt was made by Singer, who proposed a target tracking model in which maneuver was assumed by the first order Markov process with time correlation [10]. Since the Singer's method, a lot of researches have been diversely developed. One approach is related to the input estimation (IE) technique [11-15] and the others are the interacting multiple model (IMM) and the adaptive interacting multiple model (AIMM) [16-22]. Later techniques provided the better tracking performance than prior one for a maneuvering target. However, these methods have limits and additional requirements to track a maneuvering target. It is difficult to approximate acceleration adaptively because the overall process noise variance is time-varying and may be nonlinear. The IMM algorithm requires the predefined sub-models with different conditi-ons, and may not guarantee good performance in the case that one of sub-models does not exactly match the target motion. In the case of the AIMM algorithm, the accelera-tion intervals for the different acceleration levels should be determined in advance and the delay involved in estimating target's acceleration should be also treated appropriately. The most important problem in the previous studies is to increase the tracking error by considering the acceleration of a target as the simple system noise.

Motivated by the above observations, we propose a novel smart interacting multiple model (SIMM) for tracking the nonlinear maneuvering target by extracting the noise variance and the acceleration of the target. To do this, first of all, we propose the method of calculating the noise variance and acceleration of a target at every sampling time through the distance difference between the measured point and the predicted point. Then, we propose the method of tracking the nonlinear maneuvering target by calculating the velocity and position of the target through adjustment of noise variance and compensation of acceleration. Finally, we demonstrate applicability and feasibility of the proposed SIMM through the simulation.

This paper is organized as follows: Section 2 shows the maneuvering target model and briefly reviews the AIMM algorithm as the representatives of the conventional maneuvering target tracking methods. The details of the modified KF and the SIMM algorithm are described in Section 3. In Section 4, the effectiveness of the proposed intelligent tracking methods compared with the AIMM algorithm is shown. Finally conclusions are drawn in Section 5.

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2. Preliminaries

The dynamic models of the maneuvering target are described for all axes by

$$x(k+1) = Fx(k) + G[a(k) + \omega(k)], \tag{1}$$

$$z(k) = Hx(k) + v(k) \tag{2}$$

where $x(k) = [x_x(k), \dot{x}_x(k), x_y(k), \dot{x}_y(k), x_z(k), \dot{x}_z(k)]^T$ is the state vector with the position and the velocity elements for a maneuvering target. The terms *a(k)* and $\omega(k)$ are the unknown deterministic acceleration and the process noise, *z(k)* and *v(k)* are the measurement vector and the measurement noise, $\omega(k)$ and *v(k)* are considered as zero-mean white Gaussian noise sequences with variances *q* and *r*, respectively. When *t* is the sampling time, the system matrix *F*, the gain matrix *G*, and the measurement matrix *H* are specified as follows:

$$F = \begin{bmatrix} 1 & t & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & t & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & t \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad G = \begin{bmatrix} t^2/2 & 0 & 0 \\ t & 0 & 0 \\ 0 & t^2/2 & 0 \\ 0 & t & 0 \\ 0 & 0 & t^2/2 \\ 0 & 0 & t \end{bmatrix},$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}.$$

In the case of nonlinear maneuver, the deterministic unknown acceleration input of the maneuvering target is regarded as an additive process noise. Hence, (1) can be rewritten as

$$x(k+1) = Fx(k) + G\bar{\omega}(k) \tag{3}$$

where $\bar{\omega}(k) = a(k) + \omega(k)$ is assumed to be the overall proc-ess noise.

From these dynamics, previous researches dealt with the noises including unknown acceleration. A finite number of sub-models, assigned acceleration levels, and parallel structures are the required conditions. The performance of the previous algorithms was developed to a certain degree with above supports. After all, these KF-based conventional techniques cannot exceed the limit that the system appro-ximates the movement of the target adaptively including the acceleration input. Hence, we propose a novel approach which can sustain the performance in case of linear and nonlinear maneuver together in this paper.

3. SIMM Based on the Extracting Acceleration

In this section, we study the relation of the measurement point, estimated point, noise, and acceleration. Further, we investigate how the acceleration impacts on the maneuvering dynamics. With the application of the acceleration, we introduce the SIMM based on the compensating the acceleration using the maximum noise level. Using this model, we can estimate the states of the linear and nonlinear maneuvering target.

The basic idea of the compensating the acceleration arises from the fact that the primary purpose of velocity feedback is to aid in the prevention of dynamic overshoot in the tracking system. To solve this problem, it is necessary to obtain the adequate velocity with the accurate accelera-tion. In this aspect, we review the simple tracking system in the aspect of the noise and acceleration for better under-standing [5].

3.1 Review of the tracking system

Target tracking is the means by which target parameters are measured with respect to the tracking station. These parameters such as azimuth, elevation, range, and relative target velocity are ultimately employed to predict the collision between the target and whatever weapon is launched against it.

The line-of-sight (LOS) between the sensor and target is used to track the target. If the tracking element was at all times pointed directly along this LOS, tracking result would be perfect and no error would exist. Unfortunately, the tracking result of the continuous measurement is not exact and some errors are always generated in reality. Therefore a second line, the tracking line, is defined as the line that forms the axis of symmetry of the radiated energy, commonly called the antenna bore-sight axis described in Fig. 1. This error gives rise to the central problem of any tracking system. Minimizing error between the LOS and the tracking line is the most considerable factor in the tracking problem. Further target velocity data is a major input for the error of the tracking process.

Since target position data should be available to the weapon control system at all times, some means of detecting target motion is required if the sensor is to follow the target. There are two tracking and two compensating method for detecting target motion and tracking it. They are following four techniques.

1) ***Azimuth tracking***: Reverberation formulated by each beam causes azimuth error. Diminishing the error is the main purpose of the tracking. The following manners are generally used for any tracking system.

(a) Sequential lobing: A beam is positioned in one direction, and in subsequent pulses the beam is orientated slightly offset from the previous direction. There are two reflecting signals occurred with directivity in here. The tracking system acquires the optimal azimuth value when

the system finds the equilibrium point diminishing the gap between two beams as Fig. 2.

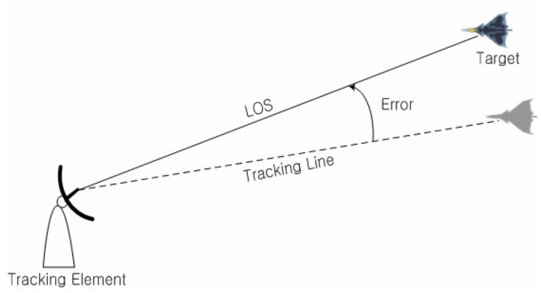


Fig. 1. Relation of LOS and track line

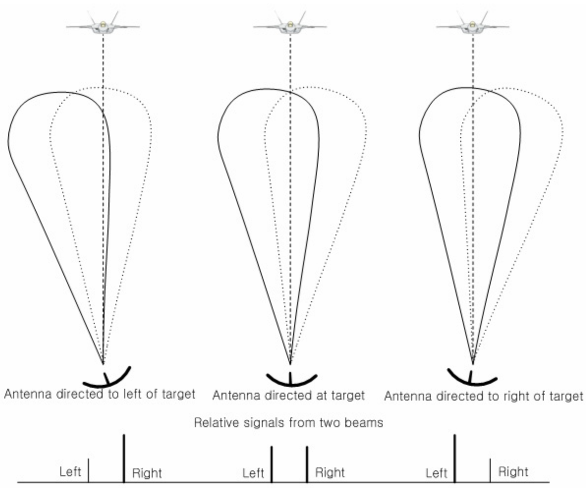


Fig. 2. Sequential lobing

(b) Conical scan: Mechanical method by rotating the feed horn in a small circle around the focal point of a fixed paraboloid. If the feed point is moved transversely away from the focus, the beam will be at an angle with the axis. If the feed point is oscillated back and forth, the beam will swing from side to side. If the feed point is rotated in a circle about the axis, a conical scan will result. If the target is not exactly on the antenna axis, an error exists between the LOS and track line. This error is immediately detectable because as the beam rotates, the return pulses are amplitude modulated due to the varying proximity of the target with the beam center.

(c) Mono pulse: Mono pulse tracking system determines amplitude modulation using only one pulse with multiple processed beams instead of a train pulses. This system uses the signal comparator circuit composed of the four feed horns producing four beams. In the circuit, four hybrids can be connected to provide azimuth and elevation error. To determine azimuth, the sum of the C and D horn outputs are subtracted from that of the A an B horns. Elevation error is determined by subtracting the sum of the outputs of the B and D horns from the sum of the outputs of the A and C horns. Simplified microwave comparator circuit of a mono pulse system in both azimuth and elevation is depicted in Fig. 3.

2) ***Range tracking*****:** The purpose of the range tracking is to follow the target in range and provide continuous distance information or slant range to the target. Range tracking is accomplished in a similar manner to dual beam angle tracking. Once the range has been measured, the tracking system attempts to predict the range on the next pulse. This estimate becomes the reference to which the next measurement will be compared. Using two range window, called the early and late range gates, makes the comparison depicted in Fig. 4.

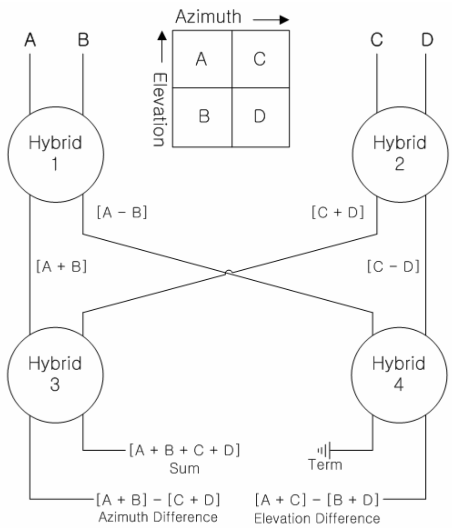


Fig. 3. Comparator circuit of mono pulse radar signal

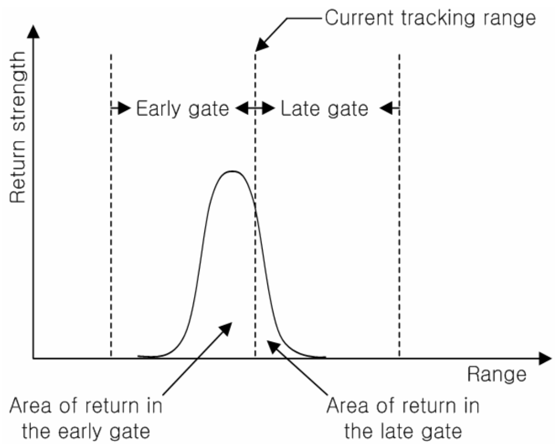


Fig. 4. Range gates

3) ***Position feedback*****:** As the system moves in response to the original error, the result is to position the tracking line in coincidence with the LOS. This action by the system reduces the position error signal until near zero, thus providing an indication that the system has responded correctly to the error initially measured by the radar. The equilibrium state of the tracking system then is a null composite error signal, resulting in zero output to the drive system. The true equilibrium state is never achieved while the system is actually tracking, but that operating properly, the system will always tend toward this state.

*4) **Velocity feedback***: The feedback voltage is subtracted from the output drive signal of the gyro. The primary purpose of velocity feedback is to aid in the prevention of dynamic overshoot.

The following algorithm for solving the tracking problem is based on the assumption that the radar provides target position information once each scan. This scheme to be implemented is the essential process for any tracking system.

*1) **Target detection***: After several scan, the tracking system processor contains what amounts to a three dimensional binary matrix representing the entire search volume of the radar. The beam splitting should meet the angular resolution less than the beam-width of the radar.

*2) **Generation of tracking gates***: A gate can be defined as a small volume of space composed of many cells meaning the three-dimensional binary matrix representing the entire search volume of the radar. If the target is within the acquisition gate on the next scan, the smaller tracking gate is generated. That gate moves to the new expected target position on subsequent scans described in Fig. 5.

A common means of dealing with a turn or linear acceleration of the maneuvering target is the turning gate.

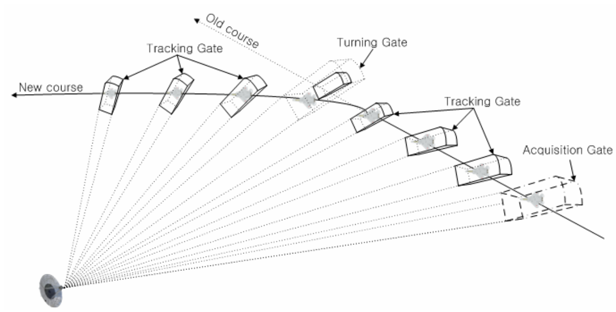


Fig. 5. Gate processing for track file

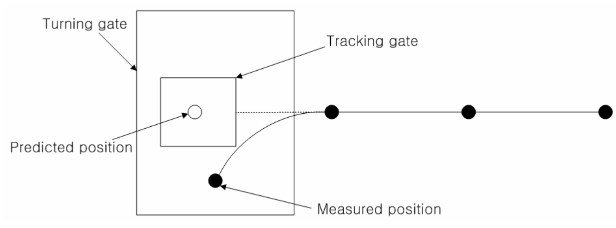


Fig. 6. Use of a turning gate

The turning gate is larger than the tracking gate and is co-located with it initially, employing separate logic and algorithms that are different from the tracking routine. The size of the turning gate is determined by the maximum acceleration and turn characteristics of valid tracks. It is described in Fig. 6.

Serious tracking errors can be generated in such a system if the return of any one pulse is markedly increased or decreased in amplitude as compared to the next pulse in the train. Such a fluctuation could easily occur if there is a sudden change on the target's radar cross section (RCS).

*3) **Target track correlation and association***: Target obser- vation on each radar scan that survives hit-pattern recognition and clutter rejection functions initially treated as new information prior to comparison with previously held data. We call it correlation with track.

*4) **Track initiation and track file generation***: Concurrent with generation of the acquisition gate, a track file is generated in order to store the position and gate data for each track. If the position data are obtained on subsequent scans of the radar, the file is updated with the coordinates, the velocities and accelerations are then computed and stored, and the acquisition gate code is canceled. The acquisition gate is then decreased in size relative to that of the tracking gate, and the track code is stored, which indicates an active track file.

*5) **Track gate prediction, smoothing, and positioning***: The system response motion was smoothed by employing rate and position feedback. The means of smoothing track data are α-β tracker, α-β filter, and the Kalman filter.

*6) **Display and future target position calculation***: We hereby show the sequence of tracking algorithm as numerical expression.

$$P_{sk} = P_k + \alpha(Z_k - P_k) \tag{4}$$

$$V_k = V_{k-1} + A_{k-1}t + \frac{\beta}{t}(Z_k - P_k) \tag{5}$$

$$A_k = A_{k-1} + \frac{\gamma}{t}(Z_k - P_k) \tag{6}$$

$$P_{k+1} = P_{sk} + V_k t + \frac{1}{2}A_k t^2 \tag{7}$$

where Z_k is target's position measured by the radar during scan k, P_{sk} is smoothed position after scan k, V_k is smoothed velocity after scan k, P_{sk} is smoothed acceleration after scan k, P_k is predicted target position for scan k, t is scan time, and α, β, γ are system constant that determine the system response, damping, and gain, respectively.

3.2 Application of the acceleration

The most important calculation of the tracking system is to diminish the error between the predicted point and the measurement point described in (4). Existing manners yield velocity by differentiating the error of Z_k and P_k and obtain the acceleration by differentiating the velocity like (4)-(7). In this case the differentiating is executed with the noise factor, so the estimated value is always accompanied noise. These manners depend on only how the system constant is set up.

A target deviates the tracking gate due to the drastic acceleration input as seen in Fig. 6. At this moment, tracking could last using the turning gate but a pretty high amount of error is inevitable for the result. If this state is repeated, the tracking element would miss the target. Many methods treating only the overhaul noise could reduce the error to some degree but it could not be a fundamental solution. The reason is like that the acceleration in the noise term plays a role of the noise with big magnitude.

The basic idea of the proposed method arises from the fact that it is difficult to directly separate acceleration from other noises because it is given with other components. So, we approximate acceleration of the maneuvering target and utilize this one to estimate the position and velocity of the target. Concerning this problem, the proposed method sets up the noise level. The error between the predicted point and the measurement point is divided by this noise level. The exceedances are regarded as approximated acceleration and the rest is regarded the mere noise. Only mere noise is on going filtering process and the filtered output is added corresponding the acceleration. Proposed method improves the system performance by taking proper action, filtering or compensation, fitting to the each factor. The filtering process can be proceeded with the less noise. A derivation of such acceleration is the subject of this section.

1) ***Extracting acceleration and compensation***: We make the maximum noise level as the permissive noise value correspond with the capability of the equipment. It means the degree of precision. This noise includes only the noisy factor like process noise and measured one. Noise only makes the error to the dynamic model. In this paper, we utilize the maximum noise level as criteria to approximate acceleration. After choosing the adequate value of a maximum noise level, we determine whether acceleration is included or not by comparing this one with the positional error between the predicted point and measured point at each sampling time.

Let us suppose a linear moving target. There is no acceleration input in this case and the target moves at regular intervals. This movement depends on only the time and velocity. When we take a look at the relation between neighboring two points, later one depends on the prior one's velocity and elapsed time like as $\dot{x}(k)\cdot\Delta t$ and the noise $\overline{\omega}$ is added to this. If we restrict the noise to a certain value, we can conjecture about the positional difference between the two points as a certain range. We can assume the maximum noise level even though we cannot get the exact process noise. It explains that the maximum noise is the value of the precision as the characteristics of the equipment.

Next, let us think of the nonlinear maneuvering case. In this case, the distance gap will be much variable by the acceleration input incurring the maneuvering. What the movement of the maneuvering target is largely varied means that the distance gap of $x(k)$ and $x(k+1)$ gets out of the range $\pm$*maximum* noise. We introduce the following assumption to distinguish acceleration input from mere noise.

Assumption 1: First, there is no correlation between measurement noise and process noise. Second, acceleration input has bigger value or smaller one than others. The reason is like that the accuracy gets higher and the error gets lower by the advance in technology.

The procedure which is approximating acceleration and compensating to the tracking dynamics is like follows. First, we get the predicted point at $t = k$ by using only the position data of the target at $t = k-1$ as follows:

$$\hat{u}(k\mid k-1)=\hat{x}(k-1\mid k-1)+\dot{x}(k-1\mid k-1)\cdot\Delta t\,. \tag{8}$$

Then, we get the error between the predicted point and measurement point as follows:

$$\hat{e}(k\mid k-1)=z(k\mid k)-\hat{u}(k\mid k-1)\,. \tag{9}$$

We approximate the maximum noise level N_{max} according to the dispersion of the errors from $t = 0$ to $t = k$. The maximum noise level is calculated with weight at every sampling time like

$$N_{max}=\frac{1}{n}\sum_{k=1}^{N}p(k)\cdot\hat{e}(k)\,. \tag{10}$$

The weight becomes bigger when the same value is repeated. If the error becomes bigger sharply, we skip the procedure because the acceleration is added. Comparing (9) with (10), we set the error as acceleration when it is bigger than N_{max} and compensate the velocity component of the by adding acceleration as follows:

$$\hat{x}(k\mid k-1)=\hat{x}(k-1\mid k-1)+\hat{a}(k\mid k-1)\cdot\Delta t\,. \tag{11}$$

When the error is smaller than the N_{max}, we regard this one as mere noise for linear maneuvering and moves on to the filtering step. We repeat this procedure at every sampling time. To make the tracking accuracy higher, we set this procedure as a sub-model of the IMM and set the N_{max} differently at each sub-model.

3.3 Proposed tracking method: SIMM

Let $\hat{x}_m(k)$ be the estimation of $x(k)$ at k based on the m_{th} sub-model and $\hat{x}(k)$ be the combined estimate from sub-filters. One cycle of the proposed algorithm is summarized as follows:

1) ***Interaction of the estimates (mixing)***: The expected mixed state estimate $\hat{x}_{0m}(k-1)(k-1)$ and its error covariance $P_{0m}(k-1\mid k-1)$ are computed from the state estimates and their error covariance of sub-filters, respectively, as foll-ows:

$$\hat{x}_{0m}(k-1\mid k-1)=\sum_{n=1}^{N}\mu_{n|m}(k-1\mid k-1)\,\hat{x}_n(k-1\mid k-1)\,, \tag{12}$$

$$\hat{P}_{0m}(k-1|k-1)=\sum_{n=1}^{N}\mu_{n|m}(k-1|k-1)\big[\hat{P}_n(k-1|k-1)$$
$$+\big(\hat{x}_n(k-1|k-1)-\hat{x}_{0m}(k-1|k-1)\big)$$
$$\times\big(\hat{x}_n(k-1|k-1)-\hat{x}_{0m}(k-1|k-1)\big)^T\big] \tag{13}$$

where the mixing probability $\mu_{n|m}$ and the normalization constant α_m are represented by

$$\mu_{n|m}(k-1|k-1)=\frac{1}{\alpha_m}\phi_{nm}\mu_n(k-1)\ , \tag{14}$$

$$\alpha_m=\sum_{n=1}^{N}\phi_{nm}\mu_n(k-1) \tag{15}$$

where $\phi_{n|m}$ is the model transition probability from the n_{th} sub-model to the m_{th} one, and $\mu_{n|m}(k-1)$ is the model probability of the n_{th} sub-model at time *k-1*.

*2) **Filtering algorithm***: Each sub-model provides a model state estimate update by the time-varying error between predicted point and measurement one as follows:

$$\hat{x}_m(k|k-1)=F\hat{x}_m(k-1|k-1)\ , \tag{16}$$
$$\hat{u}_m(k|k-1)=H\hat{x}_m(k|k-1)\ , \tag{17}$$
$$\hat{e}_m(k|k-1)=z_x(k)-\hat{u}_m(k|k-1)\ , \tag{18}$$
$$\hat{a}_m(k|k-1)=\hat{e}_m(k|k-1)/t-max\|\ \overline{w}(k)\|\ \ , \tag{19}$$
$$\hat{v}_m(k|k-1)=\hat{v}_m(k-1|k-1)+t\cdot\hat{a}_m(k|k-1)\ , \tag{20}$$
$$\hat{x}_m(k)=\hat{x}_m(k-1|k-1)+M_m(k|k-1) \tag{21}$$

where $\hat{u}_m(k)$ and $e_m(k)$ are the predicted point and the posi-tion error between measured point and predicted point at time *k*, respectively. $\hat{a}_m(k)$ and $\hat{v}_m(k)$ are the estimated acceleration and the estimated velocity to be used in calcul-ating estimate of $\hat{x}_m(k)$ at time *k*, respectively. Related matrix $M_m(k)$ at time *k* is specified as follows:

$$M_m(k|k-1)=t\begin{bmatrix}\hat{v}_m(k|k-1)\\ \hat{a}_m(k|k-1)\end{bmatrix}.$$

Also, we use KF selectively.

*3) **Computation of model likelihood***: Model likelihood $\Lambda_m(k)$ is computed by the following Gaussian function:

$$\Lambda_m(k)=\frac{1}{\sqrt{2\pi\,|S_m(k)|}}exp\Big(-\frac{1}{2}v_m^T(k)S_m^{-1}(k)v_m(k)\Big). \tag{22}$$

*4) **Update model probability***: Model probability $\mu_m(k)$ is updated according to the model likelihood and model transition probability governed by the finite-state Markov chain:

$$\mu_m(k)=\frac{\Lambda_m(k)\alpha_m}{\sum_{n=1}^{N}\Lambda_n(k)\alpha_n}. \tag{23}$$

*5) **Combination of estimates***: The combined state estimate and its error covariance are obtained from the probabilistic sum of the state estimates and their error covariances of sub-filters as follows:

$$\hat{x}(k|k)=\sum_{m=1}^{N}\mu_m(k)\hat{x}_m(k|k), \tag{24}$$

$$P(k|k)=\sum_{m=1}^{N}\mu_m(k)\big[P_m(k|k)+\big(\hat{x}_m(k|k)-\hat{x}(k|k)\big)$$
$$\times\big(\hat{x}_m(k|k)-\hat{x}(k|k)\big)^T\big]. \tag{25}$$

The proposed algorithm is illustrated in Fig. 7.

Remark 1: The proposed SIMM algorithm should be distinguished from conventional algorithms in that it has the following advantages over them. First, unlike the IMM algorithm, the proposed algorithm does not require sub-models to be predefined in terms of target maneuver properties, and can guarantee better tracking performance of the maneuvering target since the added processing error can well approximate process noise variances. Second, unlike the AIMM algorithm, the proposed algorithm could be applied to linear and nonlinear maneuver input data adaptively and sustain the capability of KF. Third, although the properties of the maneuver are unknown, the proposed algorithm can be utilized if the maneuver is within the maximum acceleration limits.

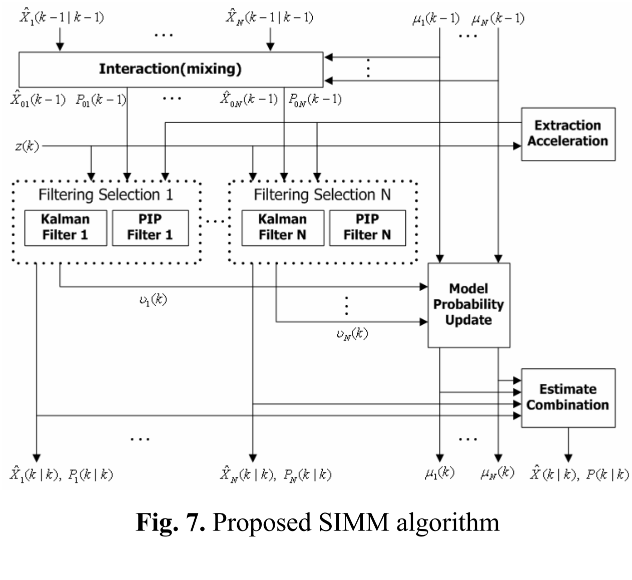


Fig. 7. Proposed SIMM algorithm

4. Simulation Results

To show the effectiveness of the proposed intelligent tracking method, we introduce a tracking scenario for an incoming cruise missile. The simulated example results of the proposed method are compared with those of the AIMM algorithm. The target is assumed as an incoming cruise missile on the 3-dimensional plane. The initial position of the target is at (100*km*, 40*km*) away on the distant horizon from the observer, and it moves with a constant velocity of 0.8856*km/sec* along a −158 degree line to x-axis.

For each axis, the standard deviation of the zero mean white Gaussian measurement noise is 0.001*km* and that of a process noise is 0.01. The sampling time t is 1*sec* and the number of iteration is 200. Maximum noise level for the proposed algorithm is 0.1, 0.01, and 0.001, respectively. The target has the lateral acceleration as shown in Fig. 8 and the corresponding target motion is determined from (1) and (2) and illustrated in Fig. 9.

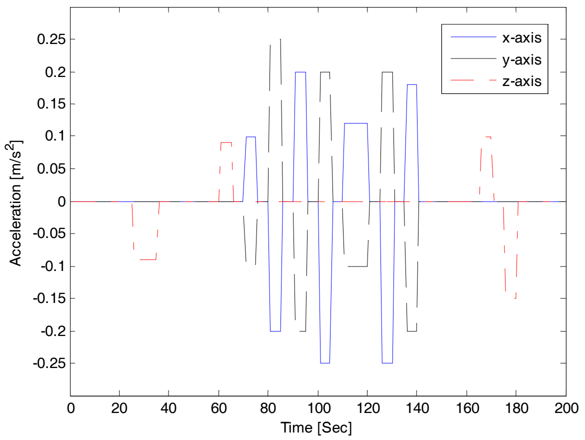


Fig. 8. Acceleration input

The proposed algorithm and AIMM have 3 sub-filters for the equal condition, respectively. The model transition probability matrix, $\phi_{n|m}$ is assumed to be

$$\phi_{nm} = \begin{cases} 0.97, & if \;\; n = m; \\ \dfrac{1-0.97}{N-1}, & \text{otherwise.} \end{cases}$$

We further assume that the initial motion of the target is similar to that from the first sub-model, so the initial model probability for each sub-model is chosen as

$$\mu_m(0) = \begin{cases} 0.6, & if \;\; m = 1; \\ \dfrac{1-0.6}{N-1}, & \text{otherwise.} \end{cases}$$

This simulation is carried out by each axis independently, and the normalized position error $P_e(k)$ and velocity one $V_e(k)$ are defined as follows:

$$P_e(k) = \frac{\sqrt{\sum_{s=1}^{N_s}\left[\left(p_x^s(k)-\hat{p}_x^s(k)\right)^2+\left(p_y^s(k)-\hat{p}_y^s(k)\right)^2+\left(p_z^s(k)-\hat{p}_z^s(k)\right)^2\right]}}{\sqrt{\sum_{s=1}^{N_s}\left[\left(p_x^s(k)-z_x^s(k)\right)^2+\left(p_y^s(k)-z_y^s(k)\right)^2+\left(p_z^s(k)-z_z^s(k)\right)^2\right]}}, \tag{26}$$

$$V_e(k) = \frac{\sqrt{\sum_{s=1}^{N_s}\left[\left(v_x^s(k)-\hat{v}_x^s(k)\right)^2+\left(v_y^s(k)-\hat{v}_y^s(k)\right)^2+\left(v_z^s(k)-\hat{v}_z^s(k)\right)^2\right]}}{\sqrt{\sum_{s=1}^{N_s}\left[\left(v_x^s(k)-\overline{v}_x^s(k)\right)^2+\left(v_y^s(k)-\overline{v}_y^s(k)\right)^2+\left(v_z^s(k)-\overline{v}_z^s(k)\right)^2\right]}} \tag{27}$$

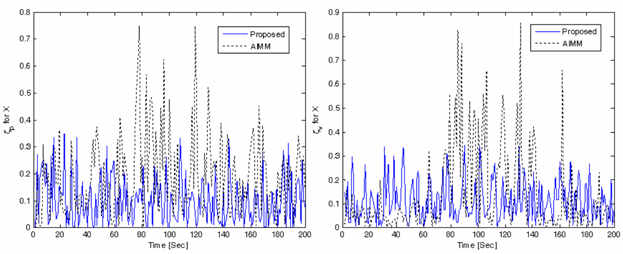
where $P_{x,y,z}^s(k)$ and $\hat{P}_{x,y,z}^s(k)$ are the true point and the estima-ted point, respectively. $Z_{x,y,z}^s(k)$ is the measured points of the target and N_s is the total number of iterations, respectively. The $v_{x,y,z}^s(k)$ and $\hat{v}_{x,y,z}^s(k)$ are the true velocities and the esti-mated velocities for each axis, respectively. $\overline{v}_{x,y,z}^s(k)$ is the velocity corresponding to the measured points of the target for each axis, respectively. For the quantitative comparison between the performances of two algorithms, we utilize the average of $P_e(k)$ and $V_e(k)$ expressed in (26) and (27) over the total number of iteration S as follows:

$$\zeta_p = \frac{\sum_{k=1}^{s} P_e(k)}{S}, \tag{28}$$

$$\zeta_v = \frac{\sum_{k=1}^{s} P_v(k)}{S}. \tag{29}$$

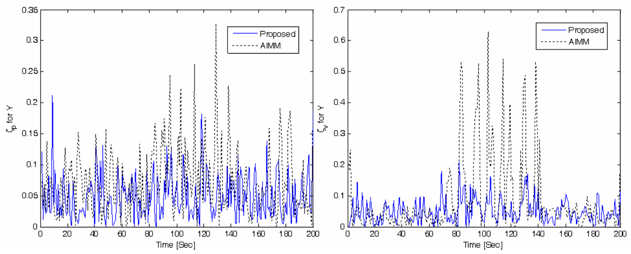
In this section, we show the simulation results for the SIMM algorithm of which performances are compared with those of the AIMM algorithm. The simulations of the proposed method are conducted by dividing into two cases, position and velocity. The simulation results over 100 runs compared with those of the AIMM method are shown by root mean square error (RMSE) in Figs. 10-12, respectively. Finally, the average result for all axes is shown in Fig. 13.

The numerical results in two cases are shown in Table 1. We can see that the proposed SIMM algorithm produces smaller position errors and velocity errors than those of the AIMM algorithm at each sampling time. Table 1 shows that it is reported that the tracking errors in position and velocity with our method are reduced by 41.16%, 28.51% compared with AIMM, in an average sense, respectively.



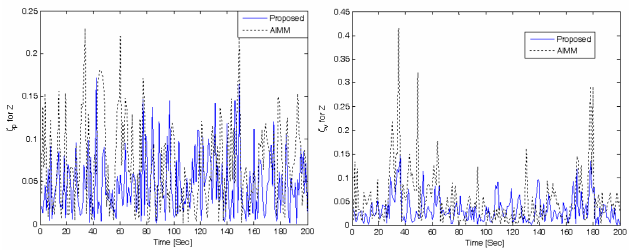
(a) Position RMSE (b) Velocity RMSE

Fig. 10. Comparisons of the position and the velocity RMSE for proposed method versus AIMM at x-axis



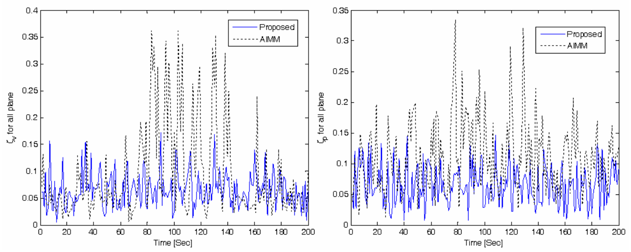
(a) Position RMSE (b) Velocity RMSE

Fig. 11. Comparisons of the position and the velocity RMSE for proposed method versus AIMM at y-axis



(a) Position RMSE (b) Velocity RMSE

Fig. 12. Comparisons of the position and the velocity RMSE for proposed method versus AIMM at z-axis



(a) Position RMSE (b) Velocity RMSE

Fig. 13. Comparisons of the position and the velocity RMSE for proposed method versus AIMM at all planes

Table 1. Comparisons of the position RMSE and the velocity one for each axis

Configuration	AIMM		Proposed	
	ζ_p	ζ_v	ζ_p	ζ_v
x-axis	0.1882	0.1358	0.0991	0.1131
y-axis	0.0718	0.0846	0.0490	0.0504
z-axis	0.0711	0.0532	0.0466	0.0321
average	0.1103	0.0912	0.0649	0.0652

This is because, although maneuvering properties are unknown, acceleration extracted by the proposed algorithm can be well approximated the time varying process noise variance and its variation at every sampling instant. On the other hand, we can see that the poor tracking performance of the AIMM algorithm arises from the uncertain estimation of complex target acceleration. Since the proposed algorithm does not require the designation of acceleration level in accordance with target maneuvers, which are prerequisites of the AIMM algorithms, it has strong potential in practical applications.

5. Conclusion

In this paper, the SIMM algorithm for tracking the maneuvering target has been proposed. In the proposed algorithm, we have calculated the positional difference between measurement point and the predicted point. Then, comparing this value with the maximum noise level, we have extracted acceleration to estimate the motion of the target. To estimate more effectively, we have constructed an optional algorithm using the proposed method and the KF selectively. The method extracting acceleration directly in the overall process noise has guaranteed better tracking performance of a maneuvering target. Also, this method has been applied effectively to linear and nonlinear maneuver while maintaining the capability of the KF. In the simulation results, one could see that the proposed intelligent tracking method shows the better performances compared with the AIMM algorithm.

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