Unscented Information Filtering with Interacting Multiple Model for Multiple Sensor Target Tracking

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(Received June 3rd, 2012)

A new method that combines an unscented information filtering (UIF) algorithm with an interacting multiple model (IMM) framework under a distributed multiple-sensor fusion architecture is proposed. The objective of the proposed scheme is to track a maneuverable target whose dynamics can be modeled with multiple nonlinear models, and whose measurements are obtained from and processed at distributed systems. An IMM is not suited for information fusion architectures because it does not use combined estimates and covariance from a previous step to predict values at the next time step, which is essential for information filtering. The proposed algorithm fuses data, such as the information state contribution and information matrix, of each UIF that is included in an IMM filter. Moreover, the proposed algorithm improves the tracking performance when the mode likelihood functions in the IMM, which are important in flight mode detection and change, are shared among the distributed systems. The tracking results from simulations indicate that the present filtering method can be a good solution to tracking of a maneuvering target in multiple-sensor environments.

Key Words: Unscented Information Filter, UIF, Interacting Multiple Model, IMM, Multiple-Sensor Data Fusion

Nomenclature

\[ E[\cdot] \]: expectation
\[ i \]: local information state contribution
\[ I \]: local information matrix
\[ N[x; \tilde{x}, P] \]: probability density function of normal random variable \( x \) with mean \( \tilde{x} \) and covariance \( P \)
\[ p[\cdot] \]: probability density function
\[ P \]: state covariance
\[ P_{zz} \]: innovation covariance
\[ P_{xz} \]: cross covariance
\[ Q \]: process noise covariance
\[ R \]: measurement noise covariance
\[ v \]: process noise
\[ w \]: measurement noise
\[ x \]: state vector
\[ y \]: information state vector
\[ Y \]: information matrix
\[ z \]: measurement vector
\[ \Lambda \]: mode likelihood function
\[ \mu \]: mode probability

Subscripts
\[ k \]: time index
\[ s \]: local sensor node

Superscripts
\[ j \]: flight mode

1. Introduction

Multiple-sensor data fusion is widely used as a method to extract useful information from measurements obtained from multiple sensors, and to utilize these in practical applications such as target tracking.

There are basically two types of sensor fusion methods for multiple-sensor target tracking: centralized fusion and distributed fusion. In a distributed fusion system, the computation or processing is carried out at different locations with local or global information, while in a centralized fusion system, all local measurements are sent to a central processor which categorizes all the available information to update the tracks using these measurements.

Distributed fusion architectures are known to have the following advantages. The processing loads at each fusion node are lighter because the processing is distributed on multiple nodes. It is not needed to maintain a large centralized database because each node has its own local database. The communication load is lower since data does not have to be sent to/from a central processing site. The survivability is higher over a central fusion node which has a single point of failure.

A distributed fusion system can exhibit variations depending on how the sensor nodes share the fusion responsibility, how the nodes communicate, and how the nodes fuse data and select their communication actions.

The information filter is one of the well-known filters for multiple-sensor fusion on linear distributed systems. It recursively performs both updates and predictions of systems states and covariance using the inverse of the covariance matrix. Compared to Kalman filter algorithms, the information filter estimation is computationally simpler and easier to initialize without a priori information on the state of systems. Another advantage of the information filter is that it can be easily adopted for multiple-sensor
estimation using a linear combination of the local information contribution terms, such as the information state contribution and information matrix.

The information filter can be extended to nonlinear systems using extended information filtering (EIF)\(^3\) through a 1st order Taylor series expansion that the extended Kalman filter (EKF) is also based on. However, EIF has shortcomings in its accuracy and robustness because it inherently contains truncation errors from the linearization process, similar to EKF. Lee\(^4\) proposed an unscented information filter (UIF) to overcome these disadvantages of EIF. The filtering algorithm was derived from the EIF architecture using an unscented transformation method that originates from the sigma point filter. It was shown that UIF could achieve not only the accuracy and robustness of the sigma point filter, but also the flexibility of the information filter for multiple-sensor estimation.

For maneuvering target tracking, multiple-model (MM) methods have been generally considered as the standard approach that includes motion-mode uncertainty.\(^5\) The interacting multiple model (IMM)\(^6\)\(^7\) is one of the most popular MM algorithms used for maneuvering target tracking.

To the best of the authors’ knowledge, a general method to use unscented information filters with IMM in a distributed system has not been proposed yet, although there are practical needs to fuse the local estimates of IMM that has nonlinear models in multiple-sensor environments. Tracking of targets is one example where the targets’ dynamics need to be modeled by multiple nonlinear models, where the measurements of the targets are obtained from multiple sensors, and where the local estimates based on those measurements from each sensor need to be fused in a distributed fusion system.

An IMM filter consists of several filters functioning in parallel, and combines the estimates of the states and covariance from each filter using mode probabilities. A drawback in the data fusion with an IMM filter is that it does not use the previous combined estimates to predict the next states and covariance, which are needed for a conventional information filter to calculate information.

This study proposes an algorithm (UIF-IMM), which combines UIF and IMM under a distributed multiple-sensor fusion architecture. The new algorithm merges information from every UIF that comprises an IMM filter rather than the combined estimates of the IMM filter. The information fused is not only the information state contribution and the information matrix, but also mode likelihood functions that play an essential role in mode detection and change.

This paper is organized as follows: An overview of UIF is presented in section 2. In section 3, the formulation of UIF-IMM is derived. The simulation results are presented in section 4, and concluding remarks are given in section 5.

2. UIF

In this section, a formulation of UIF\(^3\) is presented as a first step towards the algorithm derivation in section 3. This study employs UIF instead of a linear information filter, for tracking targets with multiple nonlinear modes. UIF can be derived by embedding an unscented transformation method, which originated from sigma point filters that include the unscented Kalman filter (UKF),\(^8\)\(^9\) into an extended information filtering architecture. A nonlinear discrete-time state space model is defined as

\[
x_{k+1} = f(x_k) + v_k \quad (1a)
\]
\[
z_k = h(x_k) + w_k \quad (1b)
\]

where, \(x_k\) is the state vector, and \(z_k\) is the measurement vector. \(v_k\) and \(w_k\) are the process noise and the measurement noise with zero mean Gaussian sequence, respectively. The corresponding covariance matrices are \(Q_k\) and \(R_k\), respectively.

First, a series of sigma points are computed with the currently estimated state (\(\hat{x}_{k|k}\)) and covariance (\(P_{k|k}\)) as Eqs. (2a)–(2c), in order to predict the state and covariance of the next frame.

\[
\chi_{0:k} = \hat{x}_{k|k}, \quad W_0 = \kappa/(n + \kappa) \quad (2a)
\]
\[
\chi_{i:k} = \hat{x}_{k|k} + (\sqrt{(n + \kappa)}P_{k|k})^i, \quad W_i = 1/[2(n + \kappa)] \quad (2b)
\]
\[
\chi_{i+n:k} = \hat{x}_{k|k} - (\sqrt{(n + \kappa)}P_{k|k})^i, \quad W_{i+n} = 1/[2(n + \kappa)] \quad (2c)
\]

where, \(\chi\) and \(W\) are, respectively, \(2n + 1\) sigma points and weights. These are computed with a scaling parameter, \(\kappa\).

The states of the sigma points are propagated and the states and covariance are computed using the unscented transformation as

\[
\hat{x}_{k+1|k} = \sum_{i=0}^{2n} W_i f(\chi_{i:k}) \quad (3a)
\]
\[
P_{k+1|k} = \sum_{i=0}^{2n} W_i \left[ f(\chi_{i:k}) - \hat{x}_{k+1|k} \right] \cdot \left[ f(\chi_{i:k}) - \hat{x}_{k+1|k} \right]^T + Q_k. \quad (3b)
\]

The predicted value of the information state vector, \(\hat{y}_{k+1|k}\), and the information matrix, \(Y_{k+1|k}\), are computed by

\[
\hat{y}_{k+1|k} = P_{k+1|k}^{-1} \hat{x}_{k+1|k} \quad (4a)
\]
\[
Y_{k+1|k} = P_{k+1|k}^{-1}. \quad (4b)
\]

The predicted observation vector, \(\hat{z}_{k+1|k}\), the innovation covariance, \(P_{k+1|k}^{zz}\), and the cross covariance, \(P_{k+1|k}^{xz}\), are predicted as follows

\[
\hat{z}_{k+1|k} = \sum_{i=0}^{2n} W_i h(f(\chi_{i:k})) \quad (5a)
\]
\[
P_{k+1|k}^{zz} = \sum_{i=0}^{2n} \left[ W_i \left( h(f(\chi_{i:k})) - \hat{z}_{k+1|k} \right) \right] \cdot \left( h(f(\chi_{i:k})) - \hat{z}_{k+1|k} \right)^T + R_{k+1} \quad (5b)
\]
\[
P_{k+1|k}^{xz} = \sum_{i=0}^{2n} \left[ W_i \left( f(\chi_{i:k}) - \hat{x}_{k+1|k} \right) \right] \cdot \left( h(f(\chi_{i:k})) - \hat{z}_{k+1|k} \right)^T. \quad (5c)
\]
The information state contribution, \( i_{k+1} \), and the associated information matrix, \( I_{k+1} \), are computed by
\[
i_{k+1} = H_{k+1}^T R_{k+1}^{-1} \left( v_{k+1} + H_{k+1} \hat{x}_{k+1|k} \right)
\approx P_{k+1|j}^{-1} P_{k+1|j}^c R_{k+1}^{-1} \left( v_{k+1} + \left( P_{k+1|j}^{-1} P_{k+1|j}^c \right)^T \hat{x}_{k+1|k} \right)
\]
\[
I_{k+1} = H_{k+1}^T R_{k+1}^{-1} H_{k+1}
\approx P_{k+1|j}^{-1} P_{k+1|j}^c R_{k+1}^{-1} \left( P_{k+1|j} T \right) \left( P_{k+1|j} \right)^{-1}
\]

where \( H_{k+1} \) is the linearized measurement matrix and \( v_{k+1} \equiv \hat{z}_{k+1|k} - h(\hat{x}_{k+1|k}) \) is the innovation vector.

The information state vector, \( \hat{y}_{k+1|k+1} \), and the Fisher information matrix, \( Y_{k+1|k+1} \), are computed in a single sensor case as follows
\[
\hat{y}_{k+1|k+1} = \hat{y}_{k+1|k} + i_{k+1}
\]
\[
Y_{k+1|k+1} = Y_{k+1|k} + I_{k+1|k+1}
\]

If measurements obtained from the sensors involved in multiple sensor fusion are synchronized, then the state is updated simultaneously with the stacked vector of all the measurements. In this case, information contribution terms have a group-diagonal structure in terms of the innovation and the measurement matrix. Therefore, update equations for multiple sensor estimation and data fusion are expressed as a linear combination of the local information contribution terms as
\[
\hat{y}_{k+1|k+1} = \hat{y}_{k+1|k} + \sum_{i=1}^{m} i_{k+1, i}
\]
\[
Y_{k+1|k+1} = Y_{k+1|k} + \sum_{i=1}^{m} I_{k+1, i}
\]

where, \( m \) is the number of sensors.

Finally, the state estimate and error covariance estimate are computed as
\[
\hat{x}_{k+1|k+1} = Y^{-1}_{k+1|k+1} \hat{y}_{k+1|k+1}
\]
\[
P_{k+1|k+1} = Y^{-1}_{k+1|k+1}
\]

3. UIF-IMM

The UIF-IMM algorithm that combines UIF and IMM in a distributed system is derived in this section. As illustrated in Fig. 1, multiple sensors \( (s = 1, \ldots, m) \) that provide synchronous observations are considered. The filter for each sensor is assumed to be an IMM filter that has multiple dynamic models \( (j = 1, \ldots, r) \). The main idea behind the UIF-IMM is to use estimates of each flight mode of the IMM for data fusion, instead of the combined estimates of the IMM. Another important aspect of the UIF-IMM is that this algorithm shares the mode likelihood function of each flight mode to enhance the performance of the flight mode detection in a multiple-sensor system. The detailed derivation of the UIF-IMM algorithm is as follows.

Fig. 1. Structure of the UIF-IMM algorithm.
First, the mixing probability, \( \mu^i_{kj,s} \), for each sensor, \( s \), is computed with the mode probability, \( \mu_k \), and the Markov mode transition probability, \( p^i \), as

\[
\mu^j_{kj,s} = p^j_{kj} \sum_{i=1}^r p^i_{kj} \mu^i_{kj,s}.
\]

Starting with \( \hat{x}_{k|0,j} \), the mixed initial condition for the filter matched to the flight mode, \( j \), is computed as

\[
\hat{x}_{0|k,j} = \sum_{i=1}^r p^i_{kj} \mu^i_{kj,s} \hat{x}_{k|0,j}.
\]

The predicted observation vector, the innovation vector, the information state vector and the Fisher information terms are computed as

\[
zz_{k|s} = p_{k+1}^{-1} \mu^j_{kj,s}^j \left( \hat{x}_{k+1|j} - \hat{x}_{k+1|j,s} \right)^T.
\]

\[
\begin{align*}
\mathcal{P}_{k+1|j} &= p_{k+1|j}^{-1} \mu^j_{kj,s}^j \left( \hat{x}_{k+1|j} - \hat{x}_{k+1|j,s} \right)^T \times \left( \hat{x}_{k+1|j,s} - \hat{x}_{k+1|j,s} \right)^T. \\
\end{align*}
\]

The information state contribution and the associated mode likelihood function for each sensor and flight mode are computed based on the UIF algorithm as

\[
\begin{align*}
&\mu^j_{kj,s} = \left( \hat{x}_{k+1|j} - \hat{x}_{k+1|j,s} \right)^T \times \left( \hat{x}_{k+1|j,s} - \hat{x}_{k+1|j,s} \right) \mu^j_{kj,s}^j \left( \hat{x}_{k+1|j} - \hat{x}_{k+1|j,s} \right)^T. \\
&I_{k+1|j} = p_{k+1|j}^{-1} \mu^j_{kj,s}^j \left( \hat{x}_{k+1|j} - \hat{x}_{k+1|j,s} \right)^T \left( \hat{x}_{k+1|j,s} - \hat{x}_{k+1|j,s} \right). \\
\end{align*}
\]

Assuming that the measurements are obtained synchronously, the information state vector and the information matrix for each flight mode of the IMM filter are updated as a linear combination of the local information contribution terms given in Eqs. (17a) and (17b),

\[
\begin{align*}
&\hat{y}_{k+1|j} = \hat{y}_{k+1|j} + \sum_{i=1}^m \hat{y}_{k+1|i}, \\
&Y_{k+1|j} = Y_{k+1|j} + \sum_{i=1}^m Y_{k+1|i}.
\end{align*}
\]

The state estimate and the error covariance for each flight mode are computed by

\[
\begin{align*}
&\hat{x}_{k+1|j} = \hat{x}_{k+1|j} + \sum_{i=1}^m \hat{x}_{k+1|i}, \\
&P_{k+1|j} = P_{k+1|j} + \sum_{i=1}^m P_{k+1|i}.
\end{align*}
\]

Once the states and the state covariance for each flight mode of each local sensor node are estimated as described above, states and state covariance are combined, respectively, using mode probability, which can be calculated using the mode likelihood functions in the IMM filter. The mode likelihood function for each flight mode in the IMM is computed for each sensor as

\[
A_{k+1|j} = p_{k+1|j}^{-1} \left( \hat{x}_{k+1|j} - \mu^j_{kj,s}^j \right). 
\]

where \( M_{k+1|j,s} \) denotes the event that model \( j \) is in effect at time \( k+1 \) for sensor \( s \), \( Z_k \) is the sequence of \( z_{il} \), \( l = 1, \ldots, k \).

As the mode likelihood function in Eq. (19) is computed with local measurements and estimates of the local measurements alone, it can be updated by fusing other local mode likelihood functions if multiple sensor measurements are available. For example, consider a track that starts to turn after a straight-line flight, and a sensor that detects the target and generates measurements. If there is another sensor that detects the target at the same time, the mode likelihood function for the turn mode associated with both measurements from the two sensors should be higher than that with measurements from one sensor. The likelihood function for each flight mode from other sensor nodes can be used for updating the local likelihood function in a manner similar to updating the state and state covariance using information from other sensor nodes. The updated local likelihood function for each flight mode is expressed as a cumulative likelihood function as
\[ A_{k+1}^j = p \left[ z_{k+1,1}, \ldots, z_{k+1,m} | M_{k+1}^j, Z_s^1, \ldots, Z_s^m \right] \]
\[ \approx p \left[ z_{k+1,1} | M_{k+1}^j, Z_s^1 \right] \cdots p \left[ z_{k+1,m} | M_{k+1}^j, Z_s^m \right] \]
\[ = \prod_{j=1}^m A_{k+1}^j, \quad \text{for each sensor site.} \] (20)

The mode probability is computed using the updated mode probability function as
\[ \mu_{k+1,j} = \frac{1}{c} A_{k+1}^j \tilde{e}_{j,s} \] (21)
where
\[ \tilde{e}_{j,s} = \sum_{i=1}^r p_{j}^i \mu_{k+1,i} c, \quad c = \sum_{j=1}^m A_{k+1,j} \]

Finally, the estimate of state and covariance for each flight mode is combined using the mode probability as follows
\[ \hat{x}_{k+1|k+1,s} = \sum_{j=1}^m \hat{x}_{k+1|k+1,j} \mu_{k+1,j} \] (22a)
\[ P_{k+1|k+1,s} = \sum_{j=1}^m \mu_{k+1,j} \left[ P_{k+1|k+1,j} + \left( \hat{x}_{k+1|k+1,j} - \hat{x}_{k+1|k+1,s} \right) \left( \hat{x}_{k+1|k+1,j} - \hat{x}_{k+1|k+1,s} \right)^T \right] \] (22b)

The structure of the UIF-IMM algorithm described here is shown in Fig. 1.

4. Simulation and Results

4.1. Simulation scenario

As a generic tracking problem, the following scenario that includes both constant velocity segments and constant turn segments is considered. The target first flies westward for 100 s at a speed of 250 knots, followed by a 3 deg/s left turn for 60 s. Then, it flies eastward for another 100 s, followed by a 2 deg/s right turn for 90 s. Then, it repeats the westward straight flight–left turn–eastward straight flight sequence. The detailed trajectory plan is shown in Table 1 and Fig. 2. The target altitude and speed are not changed during the entire simulation and there is transient time of 10 s at the end of every segment except the last segment. Three sensors provide position-only measurements synchronously with RMS errors of 30, 35, and 40 ft, respectively, in each of the two Cartesian directions (RMS errors for the horizontal positions corresponding to these are 42.4, 49.5, and 56.6 ft, respectively). The sampling interval is 1 s.

4.2. Selection of models and parameters

In order to track a maneuvering target, each local filter in a sensor site is assumed to use IMM that consists of a constant velocity (CV) model and a constant turn (CT) model.

The CV model is defined as
\[ x = [\xi, \eta, \dot{\xi}, \dot{\eta}]^T \] (23a)
\[ x_{k+1} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} x_k + \begin{bmatrix} \frac{1}{2}T^2 & 0 \\ 0 & \frac{1}{2}T^2 \\ T & 0 \\ 0 & T \end{bmatrix} v_k \] (23b)

where, \( \xi \) and \( \eta \) denote the orthogonal coordinates in the horizontal plane, and \( v_k \) is the orthogonal coordinates in the horizontal plane, and \( v_k \) is the orthogonal coordinates in the horizontal plane, and \( v_k \) is the orthogonal coordinates in the horizontal plane.

The CT model is defined as
\[ x = [\xi, \eta, \dot{\xi}, \dot{\eta}, \omega]^T \] (24a)
\[ x_{k+1} = \begin{bmatrix} 1 & 0 & \sin \omega T & -\frac{1}{\omega} \cos \omega T & 0 \\ 0 & 1 & \frac{1}{\omega} \cos \omega T & \sin \omega T & 0 \\ 0 & 0 & \cos \omega T & -\sin \omega T & 0 \\ 0 & 0 & \sin \omega T & \cos \omega T & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} x_k + \begin{bmatrix} \frac{1}{2}T^2 & 0 & 0 \\ 0 & \frac{1}{2}T^2 & 0 \\ T & 0 & 0 \\ 0 & T & 0 \end{bmatrix} v_k \] (24b)

Table 1. Trajectory plan of target.

| Segment | Start time (s) | Duration (s) | Turn rate (deg/s) |
|---------|---------------|--------------|-------------------|
| 1       | 0             | 100          | 0.0               |
| 2       | 100           | 60           | -3.0              |
| 3       | 160           | 100          | 0.0               |
| 4       | 260           | 90           | 2.0               |
| 5       | 350           | 100          | 0.0               |
| 6       | 450           | 60           | -3.0              |
| 7       | 510           | 90           | 0.0               |

Fig. 2. Trajectory of target.
where, $\omega$ is the turn rate and $v_k$ is the process noise with a zero-mean Gaussian white noise, with standard deviation $\sigma_v = 1.6 \text{ ft/s}^2$ and $\sigma_c = 0.2 \text{ deg/s}^2$.

The measurement equation is shown as

$$z = \left[ \xi_m \quad \eta_m \right]^T.$$  \hfill (25)

The measurement noise is set using the same standard deviation as that used for the simulation.

As a parameter for the IMM filter, the Markov mode transition probability matrix, $p^{ij}$, is set as

$$p^{ij} = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}. \hfill (26)$$

4.3. Simulation results

Figures 3 and 4 and Table 2 present the estimation errors of the target tracking results obtained from a Monte Carlo simulation with 100 trials, using the UIF-IMM algorithm.

In order to capture the effect of the mode likelihood function, two designs of the UIF-IMM are chosen and tested. UIF-IMM I represents the filter that implements the algorithm in section 3 except for Eq. (20), while UIF-IMM II incorporates it entirely. In order to verify the effectiveness of the present fusion algorithm, tracking results for the case with a single sensor system and a centralized fusion system are also examined.

It is obvious that multiple-sensor tracking allows for a more accurate tracking due to more measurements being processed by the UIF-IMM than a single-sensor tracking system. It is also shown that multiple-sensor fusion using the UIF-IMM algorithm with the mode likelihood function combination among the distributed sensor nodes (UIF-IMM II) has better position and course accuracies than the setup without the combination (UIF-IMM I). It should be noted that the RMS error of UIF-IMM II almost overlaps with that of the centralized fusion system. This means that the fusion of mode likelihood functions should be applied in addition to that of the states and state covariance in order to prevent information loss during fusion at the distributed system.

The mode probability estimation results are investigated in order to identify the reason behind the improved position and course accuracies with UIF-IMM II when compared to UIF-IMM I. As shown in Fig. 5, UIF-IMM II considers the cumulative likelihood function based on various sensors, and enables the filter to estimate the mode probability more precisely, which yields a more accurate fusion and estimation of the states and covariance. This conforms well with the fact that there is little difference between UIF-IMM II and the centralized fusion algorithm in mode probability, which is shown in Fig. 5.
5. Conclusion

A new algorithm for multiple sensor data fusion with a UIF algorithm combined with an IMM in a distributed system, UIF-IMM, was presented. The algorithm was designed to track maneuverable targets whose dynamics are modeled as multiple nonlinear models, and whose measurements are obtained and processed at distributed systems. An IMM needs to be handled in a nonconventional way for the information fusion because previous combined estimates and covariance of the IMM filter are not used for the predictions at subsequent steps, while the prediction of states and covariance are essential for information filtering. The proposed algorithm fuses information, such as the information state contribution and information matrix, of each UIF that comprises of individual IMM filters. Moreover, a method for the fusion of the mode likelihood functions of the IMM filter was derived and implemented in the UIF-IMM in order to improve the performance of the flight mode detection and change, and the tracking accuracy. Tracking simulations and comparison with the centralized fusion algorithm indicate that the proposed filtering method can be a good solution to tracking of a nonlinear maneuvering target in a distributed multiple-sensor environment.

Acknowledgments

This work was funded by the Ministry of Land, Transport and Maritime Affairs of Korea.

References

1) Bar-Shalom, Y.: Tracking and Data Fusion: A Handbook of Algorithm, YBS Publishing, Storrs, CT, 2011, pp. 549–578.
2) Liggins II, M., Chong, C., Kadar, I., Alford, M., Vannicola, V. and Thomopoulos, S.: Distributed Fusion Architecture and Algorithms for Target Tracking, Proc. IEEE, 85 (1997), pp. 95–107.
3) Mutambara, A. G. O.: Decentralized Estimation and Control for Multi-sensor Systems, 1st ed., CRC, Boca Raton, FL, 1998, pp. 22-32.
4) Lee, D.: Nonlinear Estimation and Multiple Sensor Fusion Using Unscented Information Filtering, IEEE Signal Proc. Lett., 15 (2008), pp. 861–864.
5) Li, X. R. and Jilkov, V. P.: Survey of Maneuvering Target Tracking. Part V: Multiple-Model Methods, IEEE Trans. Aerospace Target Tracking, 41 (2005), pp. 1255–1321.
6) Li, X. R. and Bar-Shalom, Y.: Design of an Interacting Multiple Model Algorithm for Air Traffic Control Tracking, IEEE Trans. Control Syst. Technol., 1 (1993), pp. 186–194.
7) Bar-Shalom, Y., Li, X. R. and Kirubarajan, T.: Estimation with Applications to Tracking and Navigation: Theory, Algorithms, and Software, A Wiley-Interscience Publication, New York, 2001, pp. 453–480.
8) Julier, S. J. and Uhlmann J. K.: A New Method for the Nonlinear Transformation of Means and Covariances in Filters and Estimators, IEEE Trans. Automatic Control, 45 (2000), pp. 477–482.
9) Julier, S. J. and Uhlmann, J. K.: Unscented Filtering and Nonlinear Estimation, Proc. IEEE, 92 (2004), pp. 401–422.