Data Association and Fusion Algorithms for Tracking in Presence of Measurement Loss

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Tracking in multi-sensor multi-target (MSMT) scenario is a complex and difficult task due to the uncertainties in the origin of observations. This requires appropriate gating and data association procedures to associate measurements with targets. A PC MATLAB program, based on track-oriented approach, is evaluated which uses Nearest Neighbour Kaiman Filter (NNKF) and Probabilistic Data Association Filter (PDAF) for tracking multiple targets from data of multiple sensors. For track-to-track fusion, state vector fusion philosophy is employed. The tracking performance in presence of simulated track/data loss and recovery as well as clutter is evaluated. During the data loss, the PDAF performed better than the NNKF. In the presence of mild clutter and sparse target scenarios, the NNKF and the PDAF give similar performance.

Keywords: Fusion Algorithm; Measurement loss; Uncertainty measurement; Track management

INTRODUCTION

Tracking comprises the estimation of the current state of a target, based on uncertain measurements, selected according to a certain rule as sharing a common origin and calculation of the accuracy associated with the state estimate. The problem is complex even for single target tracking because of target model and measurement uncertainties. The complexity of the tracking problem increases further when multiple targets are to be tracked from measurements of several sensors.

Data association, that is, to determine from which target, if any, a particular measurement originated, is the central problem in multi-sensor multi-target tracking. The problem is complex due to uncertain data and disparate data sources. The identity of targets responsible for each individual data set is unknown. Therefore, there is uncertainty as to how to associate data from one sensor which are obtained at one time and location to those of another sensor at another point in time and location. False alarms and the clutter detections may be present which are also not easily distinguishable from the true target measurements. In addition, one may have to deal with measurement loss in some of the tracking sensors.

Gating and data association enable tracking in multi-sensor multi-target (MSMT) scenario. Gating helps in deciding if an observation (which includes clutter, false alarms and electronic counter measures) is a probable candidate for track maintenance or track update. Data association is the step to associate the measurements to targets with certainty when several targets are in the same neighbourhood. Two approaches to data association are possible, namely, (i) Nearest Neighbour (NN) approach in which a unique pairing is determined so that at most one observation can be paired with a previously established track; the method is based upon likelihood theory and the goal is to minimize an overall distance function that considers all observation-to-track pairings that satisfy a preliminary gating test, and (ii) Decision (which is achieved using probabilistic data association PDA algorithm in which a track is updated by a weighted sum of innovations from multiple validated measurements).

For tracking in a MSMT scenario a program, based on gating and data association using both the NNKF and the PDAF approach, has been developed in PC MATLAB. This program is primarily an adapted version of software package and is updated/modified for the present application. The main features of FUSEDAT and the upgraded MSMT packages are given in Table 1. The steps in the MSMT program for multi-sensor multi-target tracking and data association are shown in Figure 1. In this article, details of algorithms (the steps in the development of the program and results of tracking for data from multiple sensors when there is measurement loss) are presented. The test scenarios considered for validating the program are given below.

- Data of three targets launched from different sites and nine sensors located at different locations tracking the targets. Three sensors are configured to track one target. In addition to the estimated target track position at the end of each scan, the program generates information on the target-sensor lock status. The performance has been evaluated by adding clutter to the data and...
simulating data loss in one or more of the tracking sensors for a short period. Results are presented in terms of track scores, innovations of the filters with theoretical bounds and computed \( \chi^2 \) distance values.

The situation where each of the three sensors looks at six targets and then all the three sensor-results are fused where there could be some data loss.

DATA ASSOCIATION AND TRACKING ALGORITHMS

In this section, the data association along with tracking Algorithms in NN Kalman Filter and Probabilistic Data Association Filter are discussed.

Table 1 Features of two packages

<table>
<thead>
<tr>
<th>NSEDAT (obtained by NAL)</th>
<th>Modified MSMT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulated data with respect to common reference point</td>
<td>(*) Simulated/Real data with respect to sensor location used and converted to common reference point in Cartesian co-ordinate frame.</td>
</tr>
<tr>
<td>NNKF/PDAF</td>
<td>NNKF and PDAF</td>
</tr>
<tr>
<td>Similar tracks combined</td>
<td>Similar tracks combined using distance threshold and track-to-track fusion</td>
</tr>
<tr>
<td>Direction of two tracks not included while combined</td>
<td>(*) No-scan approach (No = 3) used to combine similar tracks while direction of tracks taken into account. Depending on the value of No, the approach automatically takes the velocity and acceleration into account for combining similar tracks [for example, ( x(2) - x(1) ) can be regarded as velocity, etc.].</td>
</tr>
<tr>
<td>Performance metrics used</td>
<td>(<em>) Additional metrics : S-K, RMSPE (</em>) and RSSPE used</td>
</tr>
<tr>
<td>—</td>
<td>(*) Data loss feature included (measurements are removed from the data set for a fixed duration)</td>
</tr>
<tr>
<td>Target-track-oriented approach used</td>
<td>Track-oriented approach used</td>
</tr>
<tr>
<td>Clutter added</td>
<td>Clutter added</td>
</tr>
</tbody>
</table>

Note: * Some additional features

![Flow chart of the MSMT program](image)

In the NNKF, at any instant of time, the measurement that is nearest to the track is chosen for updating the track. It is to be noted that each measurement can only be associated with one track and no two tracks could share the same measurement. If invalid measurement exists, the track is updated using NN Kalman Filter. The time propagation follows the standard Kalman Filter equations which are given hereunder

\[
\tilde{X}[(k/k-1)] = \Phi \hat{X}[(k-1)/(k-1)] \\
\tilde{P}[(k/k-1)] = \Phi \tilde{P}[(k-1)/(k-1)] \Phi^T + GQG^T
\]

The state estimate is updated using

\[
\hat{X}(k/k) = \hat{X}[(k/k-1)] + K \nu(k)
\]

and

\[
\hat{P}(k/k) = (I - KH) \tilde{P}[(k/k-1)]
\]

The Kalman gain can be expressed as

\[
K = \frac{\tilde{P}[(k/k-1)]H^T S^{-1}}{S}
\]

Residual vector can be expressed as

\[
\nu(k) = z(k) - \tilde{z}[(k/k-1)]
\]

Residual covariance can also be expressed as

\[
S = HH^T + R
\]

where \( z(k) \) is the measurement vector and \( \tilde{z}[(k/k-1)] \) is the predicted value at scan \( k; H \), the measurement matrix, and \( R \) is the measurement error covariance matrix given by

\[
R = \text{diag} [\sigma_x^2 \sigma_y^2 \sigma_z^2]
\]

for the case where three observables \( x, y, z \) are considered.

If there is no valid measurement, the track retains the extrapolated value as under

\[
\hat{X}(k/k) = \tilde{X}[(k/k-1)]
\]

and

\[
\hat{P}(k/k) = \tilde{P}[(k/k-1)]
\]

The information flow in NNKF is shown in Figure 2.

Probabilistic Data Association Filter'

The Probabilistic Data Association Filter (PDAF) Algorithm calculates the association probabilities for each valid measurement at the current time to the target of interest. This probabilistic information is used in a tracking filter (PDAF) that accounts for
valid \( (m = 0) \), then
\[
\hat{X}_i(k/k) = \tilde{X}[k/(k-1)]
\]  
(10)

Combining equation (8), equation (10) and equation (7) yield the state update equation of the PDAF as follows
\[
\hat{X}(k/k) = \tilde{X}[k/(k-1)] + Ku(k)
\]  
(11)

The combined innovation is given by
\[
\nu(k) = \sum_{i=1}^{m} \rho_i(k) v_i(k)
\]  
(12)

The covariance associated with the updated state is
\[
\hat{P}(k/k) = \hat{P}[k/(k-1)] + [1 - \rho_i(k)] P^c(k/k) + P^x(k)
\]  
(13)

where the covariance of the state updated with correct measurement
\[
P^c(k/k) = \hat{P}(k/k-1) - KSK^T
\]  
(14)

and the spread of the innovations
\[
P^x(k/k) = K \left( \sum_{i=1}^{m} \rho_i(k) v_i(k)^T \nu(k) - \nu(k) \nu(k)^T \right) K^T
\]  
(15)

The conditional probability is calculated using Poisson’s Clutter Model
\[
\rho_i(k) = \frac{e^{-0.5v_i^T s^{-1} v_i}}{\lambda \sqrt{2\pi s}} \left( \frac{1 - P_D}{P_D} \right) + \sum_{i=1}^{m} \frac{e^{-0.5v_i^T s^{-1} v_i}}{\lambda \sqrt{2\pi s}} \left( \frac{1 - P_D}{P_D} \right)
\]  
(16)

where \( \lambda \) is the false alarm probability, and \( P_D \) is the detection probability.

The information flow in PDAF Algorithm is shown in Figure 3. The features of these Algorithms are given in Table 2.

**PROGRAM FOR TRACKING AND DATA ASSOCIATION ALGORITHMS FOR MSMT**

Two commonly used approaches for multi-target tracking are (i) target-oriented, and (ii) track-oriented approaches.
In the target-oriented approach, the number of targets is assumed to be known and all data association hypotheses are combined into one for each target. The track-oriented approach treats each track individually while it is initiated, updated and terminated based on the associated measurement history. The track-oriented approach is pursued for the application in this article. In the track-oriented algorithm, a score is assigned to each track and is updated according to the association history. A track is initiated based on a single measurement and is eliminated when the score is below a pre-determined threshold. A brief description of each of the steps in the program is given below.

**Sensor Attributes**

Sensor attributes include sensor location, resolution, field of view (FOV), detection probability (PD) and false alarm...
The measurements acquired from the sensors are converted using the following relationships

\[ N_f = P_f \times \mu_{FOV} \]  

(17)

where \( N_f \) is the expected number of false alarms and \( \mu_{FOV} \) is the volume of FOV.

**New Data Set**

The measurements acquired from the sensors are converted to a common reference point in a Cartesian coordinate frame using the following relationships

\[
\begin{align*}
\hat{x}_r &= \hat{x}_m - \hat{x}_o_c \\
\hat{y}_r &= \hat{y}_m - \hat{y}_o_c \\
\hat{z}_r &= \hat{z}_m - \hat{z}_o_c
\end{align*}
\]

where \( \hat{x}_r, \hat{y}_r \) and \( \hat{z}_r \) are \( x, y \) and \( z \) co-ordinates of target with respect to common reference; \( \hat{x}_o_c, \hat{y}_o_c \) and \( \hat{z}_o_c \) in the \( x, y \) and \( z \) co-ordinates of corresponding sensor location and \( \hat{x}_m, \hat{y}_m \) and \( \hat{z}_m \) are \( x, y \) and \( z \) co-ordinates of target trajectory measured by the sensors.

**Gating**

Gating is performed to eliminate unlikely measurement-to-track pairs. Assuming that the measurement vector is of dimension \( m \), a distance \( d^2 \) (normalized distance) representing the norm of the residual vector is computed using

\[ d^2 = v^T S^{-1} v \]  

(18)

For example, consider two tracks \( y_i(k-1), i = 1, 2 \) at scan \( k \). At scan \( k \), as shown in Figure 4, if four measurements \( z_j(k), j = 1, 2, 3, 4 \) are available, then the track to measurement distance \( d_{ij} \) (from \( i \)th track to \( j \)th measurement) for each of the predicted tracks \( y_i(k-1), i = 1, 2 \) is computed using equation (18). A correlation between the measurement and track is allowed if the distance \( d^2 \leq G \) where \( G \) is the \( \chi^2 \) threshold. The \( \chi^2 \) threshold is obtained from the tables of chi-square distribution since the validation region is chi-square distributed with number of degree of freedom equal to the dimension of the measurement. For those measurements that fall within the gate, the likelihood value computed using \( \log(|2\pi\hat{S}| + d^2) \) is entered in the correlation matrix [called Track to Measurement Correlation matrix (TMCR)] formed with the measurements along the rows and tracks along the columns. For those measurements that fall outside the gate, a high value is entered in the TMCR matrix (Table 3).

**Measurement to Track Association and Track Update**

When NNKF is used for tracking, the measurement that is nearest to the track is chosen for updating the track. Once the particular measurement-to-track association pair is chosen from the correlation matrix for updating track, both will be removed from the matrix and next track with the least association uncertainty will be processed. In the present example (Figure 4), measurements \( z_1(k), z_2(k) \) and \( z_3(k) \) fall within the gate region of predicted track \( y_1(k) \), \( y_2(k) \) and \( y_3(k) \) falls within the gate region of predicted track \( y_1(k) \) and \( y_3(k) \) falls outside of both \( y_1(k) \) and \( y_2(k) \) gate regions as shown in Table 3. The measurement \( z_1(k) \) is taken for updating the track \( y_1(k) \) because it is nearer than \( z_3(k) \).

In cases where PDAF is used for tracking, all measurements falling within the gate, formed around the extrapolated track and their associated probabilities are used for track updating. In present example, the measurements \( z_1(k) \) and \( z_2(k) \) are taken for updating track \( y_1(k) \) and \( y_2(k) \) is taken for updating the track \( y_3(k) \). This process continues until all tracks are considered.

**Figure 4 Diagram depicting the gating principle**

**Table 3** TMCR for two tracks \((i = 1, 2)\) and four measurements \((j = 1, 2, 3, 4)\) at scan \( k \)

<table>
<thead>
<tr>
<th>Track Measurement</th>
<th>( y_i(k) )</th>
<th>( y_j(k) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( z_1(k) )</td>
<td>( d_{11} )</td>
<td>( 1000 )</td>
</tr>
<tr>
<td>( z_2(k) )</td>
<td>( 1000 )</td>
<td>( d_{22} )</td>
</tr>
<tr>
<td>( z_3(k) )</td>
<td>( d_{13} )</td>
<td>( 1000 )</td>
</tr>
<tr>
<td>( z_4(k) )</td>
<td>( 1000 )</td>
<td>( 1000 )</td>
</tr>
</tbody>
</table>
Measurement that has not been assigned to any track will be used to initiate a new track. A score is obtained for each track based on the association history and is used in the decision of eliminating or confirming tracks.

Track Initiation

A new track is initiated with a measurement that is not associated with any existing track. A score is assigned to each initiated new track. A track is initiated by three position measurements \( (x, y, z) \) and the velocity vector. The initial score for new track is calculated using

\[
p = \frac{\beta_{NT}}{\beta_{NT} + \beta_{fa}}
\]

where \( \beta_{NT} \) is the expected number of true targets, and \( \beta_{fa} \) is the expected number of false alarm per unit surveillance volume per scan. In the present example, \( z_k(k) \) is used for track initiation.

Track Extrapolation

It is possible that a track may not have any validated measurement, in which case the track will not be updated but existing tracks are just extrapolated for processing at next scan.

Extrapolate Tracks into Next Sensor FOV

The surviving tracks in current sensor FOV are taken into next sensor FOV, because it is assumed that in MSMT scenario all sensors are tracking all targets. Also, the track score is propagated to the next sensor FOV using the Markov Chain Transition Matrix. In computing the scoring function, two models are used, one for 'observable target' (true track) designated as Model O and one for 'unobservable target' (a target outside the sensor coverage or erroneously hypothesized target) designated as model \( U \). For both models, target measurements (with detection probability \( P_D \)) as well as clutter is to be considered. It is assumed \( P_D = 0 \) for model \( U \). The models \( O \) and \( U \) are given by a Markov Chain assuming the following transition probabilities:

\[
P(M_O | M_O) = 1 - e_O, \quad P(M_U | M_O) = e_O
\]

\[
P(M_O | M_U) = 1 - e_U, \quad P(M_O | M_U) = e_U
\]

where \( M_x \) denotes the event that model \( x \) is in effect during the current sampling interval and \( \bar{M}_x \) for the previous interval. Equation (20) indicates that the transition between the models is assumed with low probabilities. The exact values of \( e_O \) and \( e_U \) are to be chosen based on the scenario under consideration.

Extrapolate Tracks into Next Scan

The surviving tracks are extrapolated for processing at next scan using target dynamic model. The target dynamic model is as follows

\[
X(k + 1) = FX(k) + Gw(k)
\]

where the target dynamic state transition matrix expressed as

\[
F = \begin{bmatrix}
1 & 0 & 0 & \Delta t & 0 & 0 \\
0 & 1 & 0 & 0 & \Delta t & 0 \\
0 & 0 & 1 & 0 & 0 & At \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
\end{bmatrix}
\]

and the state vector is given by

\[
X(k) = \begin{bmatrix}
x(k) \\
y(k) \\
z(k) \\
\dot{x}(k) \\
\dot{y}(k) \\
\dot{z}(k)
\end{bmatrix}
\]

The system noise covariance matrix can be expressed as

\[
G = \begin{bmatrix}
\frac{\Delta t^2}{2} & 0 & 0 \\
0 & \frac{\Delta t^2}{2} & 0 \\
0 & 0 & \frac{\Delta t^2}{2} \\
\Delta t & 0 & 0 \\
0 & \Delta t & 0 \\
0 & 0 & \Delta t
\end{bmatrix}
\]

and \( w(k) \) is assumed to be a zero-mean white Gaussian process noise with Covariance \( E[w(k)w(k)'] = Q(k) \) and \( At \) is the sampling interval. The extrapolation is done using the Kalman Filter equation (5).

Track Management

Many tracks can be initiated in a clutter environment. Scoring threshold is used to eliminate the false tracks. The scoring threshold is one of the system design parameters and it should be adjusted based on the scenario and performance requirement. Similar tracks are fused to avoid redundant tracks. In general, the direction of tracks has to be considered while combining similar tracks. Depending on the value of \( N_D \), this approach would automatically take the velocity as well as acceleration into account.
account for combining similar tracks [for example  \( x(2) - x(1) \) can be regarded as veloaty, etc]. A 3-scan approach has been incorporated into the program for combining the tracks. Consider two tracks whose state vector estimates and covariance matrices are given at scan \( k \):

\[
\begin{align*}
\text{track } i: & \quad \hat{X}_i(k/k), \hat{P}_i(k/k) \\
\text{track } j: & \quad \hat{X}_j(k/k), \hat{P}_j(k/k)
\end{align*}
\]  

(22)

The combined state vector can be expressed as

\[
x_c(k) = \hat{X}_i(k/k) + \hat{P}_i(k/k) \hat{P}_j(k/k)^{-1} \hat{X}_j(k/k) - \hat{X}_i(k/k)
\]

(23)

The combined covariance matrix can be expressed as

\[
P_c(k) = \hat{P}_i(k/k) - \hat{P}_i(k/k) \hat{P}_j(k/k)^{-1} \hat{P}_j(k/k)
\]

(24)

where

\[
\hat{P}(k) = \hat{P}_i(k/k) + \hat{P}_j(k/k)
\]

(25)

The logic developed finally generates the information regarding the surviving tracks and sensors to target lock status.

Graphical Display

This module displays the true trajectory and measurements and also performance measures, such as, true and false track detections, number of good and false tracks, good and false track probabilities and also the sensor and target lock status at each instant of time.

PERFORMANCE EVALUATION

The performance of the NNKF and PDAF is checked by computing the followings. The percentage fit error (PFE) in x, y and z positions can be expressed as

\[
PFE = 100 \times \frac{\text{norm}(x - \hat{x})}{\text{norm}(x)}
\]

(26)

where \( x \) is the true x-position data and \( \hat{x} \) is the estimated x-position data.

The root mean square position error (RMSPE) can be expressed as

\[
\text{RMSPE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i - \hat{x})^2 + (\hat{y}_i - \hat{y})^2 + (\hat{z}_i - \hat{z})^2}
\]

(27)

The root sum square position error (RSSPE) is calculated as follows

\[
\text{RSSPE} = \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2 + (z - \hat{z})^2}
\]

(28)

Singer-Kanyuck track association metric can be expressed as

\[
C_{ij} = \frac{\left| \hat{x}_i - \hat{x}_j \right|^2}{(\hat{p}_i + \hat{p}_j)^{-1}}
\]

(29)

The metric \( C_{ij} \) can be viewed as the square of the (normalized) distance between two Gaussian distributions with mean vectors \( \hat{x}_i \) and \( \hat{x}_j \) and a common covariance matrix \( P_i + P_j \).

Percentage root mean square position error can be calculated using the following relationship

\[
\text{RMSPE}\% = \frac{\text{RMSPE}}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i - \hat{x})^2 + (\hat{y}_i - \hat{y})^2 + (\hat{z}_i - \hat{z})^2}} \times 100
\]

(30)

RESULTS AND DISCUSSION

The interactive program for MSMT data association and tracking is used to identify which of the sensors in the MSMT scenario are tracking same targets using the scenario of nine sensors located at different points in space and their measurements. Figure 5 shows the trajectories as seen from nine sensors. At each scan, the program displays the target identification (ID) and the sensors, which are tracking that particular target on the screen. It is found that initially nine tracks survive before similar tracks are combined using a predetermined distance threshold. After this combination, it is seen that only three tracks survive and they have been assigned three target ID numbers (T1, T2 and T3). The sensors, which track a particular target, are given in Table 4 from which it is clear that three sensors track one target.
Track loss is simulated in data from sensors 1-3 during 100 s - 150 s. Figure 6 shows the data with simulated clutter ($P_fa = 10^{-15}$) added to the sensor data. It is clear from the Table 5 that the performance of the two data association algorithms in the presence of clutter for this scenario is almost identical. The comparison of true tracks and estimated tracks with NNKF is shown in Figure 7. Figure 8 shows the track score, the innovations with bounds and the $\chi^2$ distance measure on the X-axis data for target/track-1 (indicated as T1X in Figure 8) where there is data loss and for target/track-2 (indicated as T2X in Figure 8) where there is no data loss. The track score is zero during the measurement data loss.

### Table 4 Target and corresponding tracking sensor identification (Id) numbers

<table>
<thead>
<tr>
<th>Target Number</th>
<th>Sensor Id</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>S1, S2, S3</td>
</tr>
<tr>
<td>T2</td>
<td>S4, S5, S6</td>
</tr>
<tr>
<td>T3</td>
<td>S7, S8, S9</td>
</tr>
</tbody>
</table>

### Table 5 Percentage fit error in track positions

<table>
<thead>
<tr>
<th>Track Number</th>
<th>NNKF</th>
<th>PDAF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PFE in x</td>
<td>PFE in y</td>
</tr>
<tr>
<td>Track 1</td>
<td>0.0604</td>
<td>0.0557</td>
</tr>
<tr>
<td>Track 2</td>
<td>1.0398</td>
<td>1.0491</td>
</tr>
<tr>
<td>Track 3</td>
<td>0.0522</td>
<td>0.0283</td>
</tr>
</tbody>
</table>

Figure 6 Measurement data with simulated clutter (converted to a common reference location)

Figure 7 Comparison of estimated trajectories with the true trajectories

Figure 8 Performance evaluation measures

Figure 9 RSSPE in track-1 without data loss

Figure 10 RSSPE in track-1 with data loss
innovations are within the theoretical bounds and the $\chi^2$ distance values at each scan are below the threshold values obtained from the $\chi^2$ tables. Figure 9 and Figure 10 show the RSSPE in track-1 without and with data loss, respectively. The RSSPE is very large during the data loss segment as shown in Figure 10. The PFE and the percentage RMSPE when there is a data loss in track-1 are given in Table 6. It is observed from the table that the PFE and RMSPE (%) increase as the duration of data loss increases. The Singer-Kanyuck association metric for $i$th track and $j$th track from the same target are almost zero, which means that the association is feasible. The association metric for $i$th track and $j$th track from different targets are shown in Figure 11. The metric is large, which means that the association is infeasible. It is seen from Figure 12 and Figure 13 that the performance of PDAF is better than that of NNKF in presence of data loss. The data loss for longer time may be acceptable if PDAF is used since it gives lower PFE and RMSPE. Figure 14 and Figure 15 show the results of data fusion of three sensors and six targets and associated performance aspects like track probability, good tracks, etc with 20 Monte-Carlo simulation runs. The need for considering the $N_D$-direction approach while combining the similar tracks is explained with the help of Figure 16. The test scenario is generated by keying in the x-y co-ordinates and then using in MSMT software. The estimated trajectories with/without $N_D$-direction approach are shown. It is observed from Table 7 that both the PFE and the RMSPE are high when the $N_D$-direction approach is not considered.

**Table 6** PFE and RMSPE (%) at data loss in track 1 (distance in meters)

<table>
<thead>
<tr>
<th>Data Loss (in s)</th>
<th>NNKF</th>
<th>PDAF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PFE</td>
<td>RMSPE</td>
</tr>
<tr>
<td>0</td>
<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>5</td>
<td>1.32</td>
<td>1.41</td>
</tr>
<tr>
<td>10</td>
<td>2.04</td>
<td>2.13</td>
</tr>
<tr>
<td>20</td>
<td>3.62</td>
<td>3.78</td>
</tr>
<tr>
<td>30</td>
<td>5.65</td>
<td>5.80</td>
</tr>
</tbody>
</table>

**Table 7** PFE and RMSPE (%) without and with direction of track considering while combined with similar tracks

<table>
<thead>
<tr>
<th>Track</th>
<th>Without Direction</th>
<th>With Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PFE (%)</td>
<td>RMSPE (%)</td>
</tr>
<tr>
<td>x</td>
<td>y</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.62</td>
<td>2.35</td>
</tr>
<tr>
<td>2</td>
<td>6.26</td>
<td>16.0</td>
</tr>
</tbody>
</table>

**Figure 12** PFE with data loss

**Figure 13** Percentage RMSPE with data loss
Figure 14 Simulated scenario having six-targets tracked by three-sensors (data loss)
Figure 15 Performance evaluation measures for scenario of Field 14

Figure 16 The need for N_D-direction approach while combining similar tracks
CONCLUSION

A PC MATLAB program, based on track-oriented approach, has been evaluated using NNKF and PDAF for tracking multiple targets from data of multiple sensors. The performance in the presence of simulated track loss and recovery as well as in clutter is evaluated using the simulated data. During data loss, PDAF performed better than NNKF. In the presence of mild clutter and sparse target scenarios, the NNKF and PDAF give similar performance. The MSMT program could be made commercially available.

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