TRACKING OF MULTIPLE TARGETS USING INTERACTIVE MULTIPLE MODEL AND DATA ASSOCIATION FILTER

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Abstract

Tracking of multiple targets using interactive multiple model and data association filter has been developed on PC MA TLAB. The performance of the algorithm is evaluated in terms of estimated and measured tracks in presence of clutter, mode probability, standard deviation, root mean square position error and with varieties of simulated scenarios. Sensitivity of the algorithm to the choice of tracking models and process noise covariance values has been studied. This algorithm has also been evaluated for multi sensor multi target scenario using fusion technique. It was observed that interactive multiple model probabilistic data association filter gives a realistic confidence in the estimates during maneuvers and lower RSSPE during the non-maneuvering phase of the targets.

Introduction

Target tracking comprises of 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 and credibility 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 multiple sensors [1,2].

Target tracking using sensor measurements in clutter is of interest in military applications such as radar and sonar systems, indigenous missile testing, tracking different hostile missiles, aircraft and helicopters. It has also found use in nonmilitary applications such as robotics, air traffic control and surveillance. In practice, scenarios for target tracking could include maneuvering targets, crossing targets and splitting targets. Various algorithms are applied to achieve target tracking in these scenarios and the selection of the algorithms is highly application dependent. In general, kinematic quantities like position, velocity and acceleration are of interest in target tracking. The target track is updated by correlating measurements with the existing tracks or initiating new tracks by using measurements coming from different sensors. Data association is the step to associate the measurements to the targets with certainty when several targets are in the same neighborhood. In practice, measurements arriving from the sensors may not be true due to clutter, false alarms, and interference from other targets, limited resolution capability (spatial coverage limitation of the sensor) and several targets in neighborhood.

The commonly used algorithms for multi sensor multi target (MSMT) tracking in clutter are nearest neighborhood Kalman filter (NNKF), Probabilistic data association filter (PDAF), interactive multiple model PDAF (IMMPDAF) and multiple hypothesis tracking (MHT). In this paper, the performance of IMMPDAF for estimation of multiple maneuvering target trajectories in clutter is investigated. Simulated data of two maneuvering targets in clutter tracked by single sensor are used for the evaluation. Sensitivity of the IMMPDAF to the choice of the tracking models and process noise covariance values is evaluated. Results are presented in terms of root sum squares position error (RSSPE), standard deviations of the estimates and maneuvering mode probabilities. Results of using the IMMPDAF algorithm for tracking and fusion of simulated data of four targets whose positions are measured by two sensors located at different spatial positions are also presented in the paper.

Gating

Gating is a technique for eliminating unlikely observation-to-track pairings. Gates (mostly rectangular, circular or ellipsoidal in shape) are defined for one or more existing tracks and if an observation satisfies the gates, it

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becomes a candidate for association with that track (Fig.1). The region enclosed by the gate is called the validation region. Any of the following situations may be encountered during gating -

- More than one observation may satisfy the gate of a single track
- The observation may satisfy the gates of more than one existing tracks
- The observation might not ultimately be used to update an existing track even if it falls within the validation region. Thus it may be used to initiate a new track.
- The observation might not fall within the validation region of any of the existing tracks. In such a case, it is used to initiate a new tentative track.

If **z(k)** is the measurement at scan *k* given by

$$z(k) = Hx(k) + v(k) \quad (1)$$

and $y = H\hat{x}(k \mid k-1)$ is the predicted value with $\hat{x}(k \mid k-1)$ representing the predicted value of the state at scan (k-1), then the residual vector (or innovation) is given by

$$v\mathbf{(k) = z(k) - y(k)} \quad (2)$$

The residual covariance matrix *S* is given by

$$S = HPH^{\mathbf{T}} + \mathbf{R} \quad (3)$$

where **R** is the measurement noise covariance matrix. Assuming the measurement vector of dimension *M*, a distance $\mathbf{d}^2$ representing the norm of the residual vector is defined as follows

$$d^2 = v^T \mathbf{S}^{-1} v \quad (4)$$

A correlation between the observation and track is allowed if the distance $\mathbf{d}^2$ is less than a certain gate threshold, i.e.,

$$d^2 = v^T \mathbf{S}^{-1} v \leq \mathbf{G} \quad (5)$$

The observation falling within the above-defined gate is more likely to be from the track rather than from any other extraneous source. A simple method to choose G is based on chi-square distribution with M degrees of freedom. The distance $\mathbf{d}^2$ is the sum of the squares of M

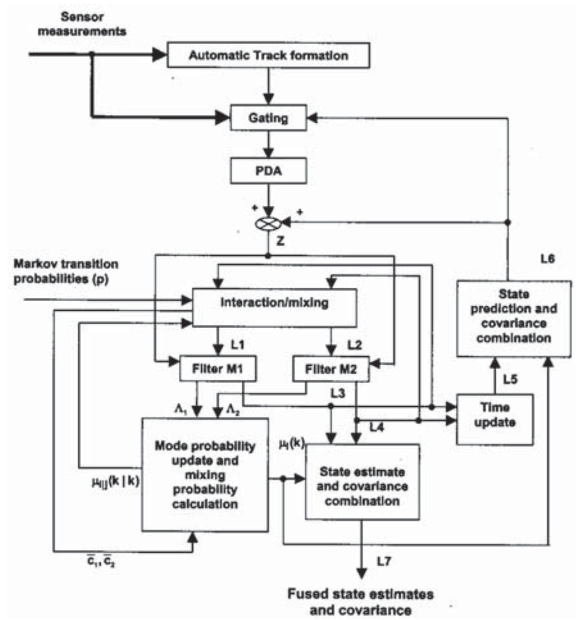

Fig. 1 A 2-model IMMPDAF scheme

independent Gaussian variables with zero means and unit standard deviations. As such, the quadratic form of $\mathbf{d}^2$ has a chi-square distribution and a gate on $\mathbf{d}^2$ can be determined using chi-square Tables [1].

For the results presented in this paper, an ellipsoidal gate is used. The parameters of the ellipse (semi major and semi minor axis length σ_x and σ_y) are given by the square root of the diagonal elements of innovation covariance matrix (for two dimensional gate).

Data Association

In a multi-target scenario, gating provides only a part of the solution to the problem of track maintenance and track update. Additional logic is required when an observation falls within the gates of multiple tracks or when multiple observations fall within the gate of a single track. Several techniques are available to handle data association problem, the most popular among them being the Nearest Neighborhood (NN) and Probabilistic Data Association (PDA) algorithms [1]. In present work, a PDAF algorithm is combined with IMM approach in order to track maneuvering targets.

Probabilistic Data Association (PDAF)

Unlike NNKF, which considers only one of the validated measurements for data association, the PDAF algorithm calculates the association probabilities for each measurement lying in the validation region. PDAF is like standard Kalman filter with the exception of two additional blocks for computation of association probabilities β_i (**k**) and combined innovations **v(k)**. If $\mathbf{v}_i\mathbf{(k)}$ corresponds to innovation on measurement *i*, then the combined innovation is given by

$$v(k) = \sum_{i=1}^{m(k)} \beta_i \,(\mathbf{k})\mathbf{v_i}\,(\mathbf{k}) \tag{6}$$

where **m(k)** denotes the number of detections in kth scan.

Probability $\beta_i(\mathbf{k})$ that the *i*-th validated measurement is correct one is given by

$$\beta_i\,(\mathbf{k}) = \begin{cases} \dfrac{e_i}{b + \sum_{j=1}^{m\,(k)} \boldsymbol{e}_j} & i = 1,2,\ldots,\, m\,(k) \\ \dfrac{b}{b + \sum_{j=1}^{m\,(k)} \boldsymbol{e}_j} & i = 0 \end{cases} \tag{7}$$

where $\beta_0(\mathbf{k})$ is the probability that none of the measurements are correct.

In equation 7, $$\mathbf{e}_i \cong \mathbf{e}^{\frac{1}{2} v_i\,(k)'S\,(k)^{-1}\, v_i(k)} \tag{8}$$

and $$\mathbf{b} \cong \left(\frac{2\pi}{\gamma}\right)^{\frac{n_z}{2}} \mathbf{m}\,(\mathbf{k})\, \mathbf{c}_{n_z}^{-1}\, \frac{(\mathbf{1} - \mathbf{P_D P_G})}{\mathbf{P_D}} \tag{9}$$

where $\mathbf{n}_z$ is the dimension of the measurement, $\mathbf{c}_{nz}$ is the volume of the unit hypersphere of this dimension ($c_1 = 2$, $c_2 = \pi$, $c_3 = 4\pi/3$, etc) and $\mathbf{P}_G$ and $\mathbf{P}_D$ represent the gate probability and probability of target detection, respectively. The computed $\beta_i(\mathbf{k})$ and **v(k)** are then used to estimate the state and covariance of the updated state.

Since, PDAF uses all the measurements falling in the validation region for data association, it is also called an "all-neighbors modified filter". There are less chances of track loss with PDAF than with NNKF.

Interacting Multiple Model (IMMPDAF)

Interactive Multiple Model (IMM) [2,4] is an extremely versatile tool for adaptive state estimation in systems whose behavior changes with time. This approach assumes that the system obeys one of a finite number of models. Two or more models are run in concurrence (only in case of parallel computer implementation) to achieve better tracking performance of maneuvering targets. The features of IMM are combined with PDAF described above to develop the IMMPDAF algorithm, which is described below.

Figure 1 illustrates one cycle of a 2-model IMMPDAF algorithm, which is applicable to single sensor multi target scenario. This could be extended to multi sensor scenarios as well. Fig.2 shows the block schematic of the MSMT fusion algorithm. The IMMPDAF algorithm has six major steps:

Automatic track formation:

The main objective of track initiation is to calculate initial state estimates of all possible tracks and compute the associated state covariance matrix. In practice, there is every possibility of generating false tracks due to the presence of spurious measurements and multiple targets.

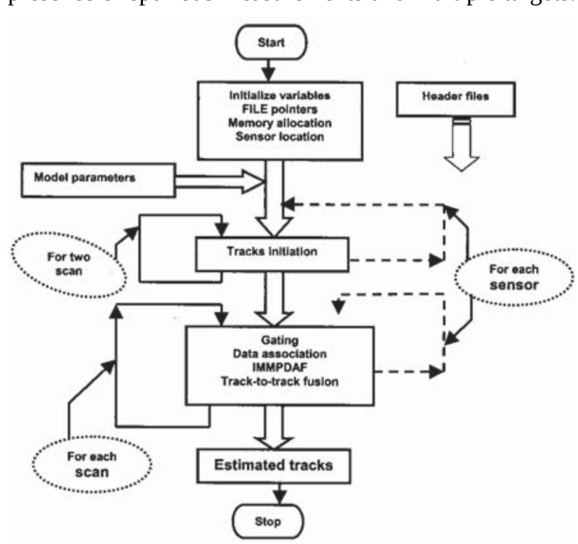

Fig. 2 Block schematic - MSMT fusion

A commonly used technique to initiate track is based on a logic that requires M detections out of N scans in the gate. In this approach, a tentative track is formed on all two-measurement pairs with expected motions of targets of interest.

Gating and data association:

After the track formation, measurement screening is carried out using eqs. 2-5 to get potential candidates for corresponding tracks. The combined innovation sequence v is computed using eqs. 6-9. The resultant measurement, used in mode conditioned filtering, is computed using:

$$\mathbf{Z(k) = H\tilde{X}\ (k/k-1)} + v(\mathbf{k}) \tag{10}$$

where, $\mathbf{\tilde{X}\ (k/k-1)}$ is predicted target states at k[th] scan and is computed from state and covariance prediction block (see Fig.1-L6).

Interaction and mixing (L1 and L2):

Using the mixing probabilities $\mu_{i|j}\ \mathbf{(k-1|k-1)}$ as weighting factors, the estimates of $\mathbf{\hat{X}_i\ (k-1|k-1)}$ and $\mathbf{\hat{P}_i\ (k-1|k-1)}$ from the previous cycle are used to obtain the initial conditions $\mathbf{\hat{X}_{0j}\ (k-1|k-1)}$ and $\mathbf{\hat{P}_{0j}\ (k-1|k-1)}$ for the mode-matched filters $\mathbf{M}_1$ and $\mathbf{M}_2$ of the current cycle (See Fig.1)

For all $\mathbf{i, j} \in \mathbf{M}$, the initial conditions for the filters are given by

$$\mathbf{\hat{X}_{0j}\ (k-1|k-1)} = \sum_{i=1}^{r} \mathbf{\hat{x}_i\ (k-1|k-1)\ \mu_{i|j}\ (k-1|k-1)} \tag{11}$$

$$\mathbf{P_{oj}\ (K-1|K-1)}$$

$$\sum_{i=1}^{r}\begin{bmatrix} P_i(k-1 \mid k-1 + \\ [\{\hat{X}_i(k-1 \mid k-1) - \hat{X}_{oj}(k-1 \mid k-1)\} \times \\ \{\hat{X}_i(k-1 \mid k-1) - \hat{X}_{oj}(k-1 \mid k-1)\}^T\ ] \end{bmatrix} \mu_{i|j}\ (k-1 \mid k-1) \tag{12}$$

where the time index is given by $\mathbf{k}$; mode-matched filters $\mathbf{j=1,..., r}$; models $\mathbf{i=1}, ..., \mathbf{r}$; $\mathbf{r = 2}$ for the 2-model IMM approach; $\mathbf{\hat{X}_i\ (k|k)}$ and $\mathbf{P_i\ (k|k)}$ are the state estimate and covariance in mode i; and $\mathbf{\hat{X}_{0j}\ (k|k)}$ and $\mathbf{P_{0j}\ (k|k)}$ are the mixed initial conditions for filter $\mathbf{j}$ at time k.

Mode conditioned filtering (L3 and L4) :

With r parallel mode-matched Kalman Filters (r = 2 for 2-model IMM), the states and covariances are estimated using the standard prediction and update steps.

$$\begin{aligned}
\mathbf{\hat{X}_j\ (k \mid k-1)} &= \mathbf{F_j\ (k-1)\ \hat{X}_{0j}\ (k-1 \mid k-1)} \\
&\quad + \mathbf{G_j\ (k-1)\ w_j\ (k-1)} \\
\mathbf{P_j\ (k \mid k-1)} &= \mathbf{F_j\ (k-1)\ P_{0j}\ (k-1 \mid k-1)\ \ F_j\ (k-1)^T} \\
&\quad + \mathbf{G_j\ (k-1)\ Q_j\ (k-1)\ G_j\ (k-1)^T} \\
\mathbf{\hat{X}_j\ (k \mid k)} &= \mathbf{\hat{X}_j\ (k \mid k-1) + K_j\ (k)\ v_j\ (k)} \\
\mathbf{P_j\ (k \mid k)} &= \mathbf{P_j\ (k \mid k-1) - K_j\ (k)\ S_j\ (k)\ K_j\ (k)^T}
\end{aligned} \tag{13}$$

If the measurement at time k is given $\mathbf{Z(k)}$, the measurement prediction $\mathbf{\hat{Z}_j\ (k \mid k-1)}$ is given by the relation

$$\mathbf{\hat{Z}_j\ (k \mid k-1) = H_j\ (k)\ \hat{X}_j\ (k \mid k-1)} \tag{14}$$

The residual $\mathbf{v_j(k)}$, residual covariance $\mathbf{S_j(k)}$ and the filter gain $\mathbf{K_j(k)}$ in eq. 13 are given by

$$\begin{aligned}
\mathbf{v_j\ (k)} &= \mathbf{Z\ (k) - \hat{Z}_j\ (k \mid k-1)} \\
\mathbf{S_j\ (k)} &= \mathbf{H_j(k)\ P_j\ (k \mid k-1)\ H_j\ (k)^T + R_j\ (k)} \\
\mathbf{K_j\ (k)} &= \mathbf{P_j\ (k \mid k-1)\ H_j\ (k)^T\ S_j\ (k)^{-1}}
\end{aligned} \tag{15}$$

The structure of the system given by $\mathbf{F}$ and $\mathbf{H}$ matrices, and the process and measurement noise covariance matrices given by $\mathbf{Q}$ and $\mathbf{R}$, can differ from mode to mode.

The likelihood function for mode-matched filter $\mathbf{j}$ is a Gaussian density function of residual v with zero mean and covariance S. It is computed as follows

$$\Lambda_j\ (K) = \frac{1}{\sqrt{|\,S_j\ (k)\,|}\ \ (2\pi)^{n/2}}\ e^{-0.5\ [v_j(k)^T S_j(k)^{-1} v_j(k)]} \tag{16}$$

where n denotes the dimension of the measurement vector $\mathbf{Z}$.

Probability Evaluations :

The mixing probabilities to be used in eqs. 11 and 12 are computed as follows:

$$\mu_{i|j}\,(\mathbf{k-1|k-1}) = \frac{1}{\bar{\mathbf{c}}_{\mathbf{j}}}\,\mathbf{p_{ij}}\,\mu_{\mathbf{i}}\,(\mathbf{k-1}) \tag{17}$$

where,

$$\bar{\mathbf{c}}_{\mathbf{j}} = \sum_{\mathbf{i=1}}^{\mathbf{r}} \mathbf{p_{ij}}\,\mu_{\mathbf{i}}\,(\mathbf{k-1}) \tag{18}$$

$\mu_i(\mathbf{k})$ is the mode probability at time k and $\bar{\mathbf{c}}_j$ is a normalization factor. $\mathbf{p}_{ij}$ is the Markov transition probability which takes care of switching from mode **i** to mode **j**. This is a design parameter and is chosen by the user. The switching probabilities are generally known to depend upon *sojourn* time. For example, consider the following Markov chain transition matrix between the two modes of the IMM

$$\boldsymbol{P_{ij}} = \begin{bmatrix} \mathbf{0.9} & \mathbf{0.1} \\ \mathbf{0.33} & \mathbf{0.67} \end{bmatrix}$$

The basis for selecting $\mathbf{p}_{12}$ = 0.1is that, in the initial stages, the target is likely to be in non-maneuvering mode and probability to switch over to maneuvering mode will be relatively low. On the other hand, $\mathbf{p}_{22}$ is selected based on the number of sampling periods for which the target is expected to maneuver (*sojourn* time). If the target maneuver lasts for 3 sample periods ($\tau = 3$), the probability $\mathbf{p}_{22}$ is given by

$$p_{22} = 1 - \frac{1}{\tau} = 0.67 \tag{19}$$

To compute $\mu_{i|j}$ (k|k) and $\bar{\mathbf{c}}_j$ in eqs. 17 and 18 in the first cycle of estimation algorithm, the initial mode probabilities $\mu_i(\mathbf{k})$ corresponding to non-maneuver and maneuver mode can be taken as 0.9 and 0.1, respectively. This selection is based on the assumption that the target is more likely to be in non- maneuver mode than in maneuver mode during the initial stages of target motion. For subsequent computations, the mode probabilities are updated using the following relation

$$\mu_j(\mathbf{k}) = \frac{\mathbf{1}}{\mathbf{c}}\,\Lambda_{\mathbf{j}}(\mathbf{k})\bar{\mathbf{c}}_{\mathbf{j}} \qquad \mathbf{j = 1,...,r} \tag{20}$$

where $\Lambda_j(\mathbf{k})$ represents the likelihood function corresponding to filter **j** (see eq. 16) and the normalizing factor **c** is given by

$$\mathbf{c} = \sum_{\mathbf{j=1}}^{\mathbf{r}} \Lambda_{\mathbf{j}}\,(\mathrm{k})\,\bar{\mathbf{c}}_{\mathbf{j}} \tag{21}$$

Combined state and covariance prediction/ estimation (L6 and L7) :

Prediction (L6) : The average mode probabilities obtained in eq. 20 are used as weighting factors to combine the predicted the state and covariance (**L5**) from eq. 22, for all filters (**j = 1, ..., r**), to obtain overall state estimate and covariance prediction (used in gating).

$$\tilde{X}_j(k+1 \mid k) = F_j\,(k)\,\hat{X}_j\,(k \mid k)$$

$$\tilde{P}_j\,(k+1 \mid k) = F_j\,(k)\,\hat{P}_j\,(k \mid k)F_j(k)^T +$$

$$G_j(k)Q_j(k)G_j(k)^T;\ j = 1,...,r \tag{22}$$

$$\tilde{X}(k+1 \mid k) = \sum_{j=1}^{r} \tilde{X}_j\,(k+1 \mid k)\,\mu_j\,(k)$$

$$\tilde{P}(k+1| k) = \sum_{j=1}^{r} [\tilde{P}_j\,(k+| k) + \left\{\tilde{X}_j\,(k\ +1| k) - \tilde{X}\,(k) + 1| k)\right\}$$

$$\left\{\tilde{X}_j\,(k+1 \mid k) - \tilde{X}\,(k+1 \mid k)\right\}^T]\,\mu_j\,(k) \tag{23}$$

Estimate (L7) : The average mode probabilities obtained in eq. 20 are also used as weighting factors to combine the updated state and covariance from eq. 13, for all filters ($j = 1, ..., r$), to obtain overall state estimate and covariance.

$$\hat{X}(k \mid k) = \sum_{j=1}^{r} \hat{X}_j\,(k \mid k)\,\mu_j\,(k)$$

$$P(k| k) = \sum_{j=1}^{r} [P_j\,(k \mid k) + \left\{\hat{X}_j\,(k \mid k) - \hat{X}\,(k) \mid k)\right\}$$

$$\left\{\hat{X}_j\,(k \mid k) - \hat{X}\,(k \mid k)\right\}^T]\,\mu_j\,(k) \tag{24}$$

Data Simulation

Data of multiple maneuvering targets in clutter are simulated using PC MATLAB. The target motion is simulated using a 2^{nd} order constant velocity model during the non-maneuvering phase of the target motion and a 3^{rd} order constant acceleration model during the maneuvering phase of the target.

The target motion model is described in the Cartesian coordinate system by linear discrete-time difference equation with additive noise:

$$X(k+1) = FX(k) + Gw(k) \tag{25}$$

$$Z(k) = HX(k) + v(k) \tag{26}$$

where the Cartesian state vector **X** consists of the position and velocity of the target moving in 2D space (i.e. $\mathbf{X = [x \;\; \dot{x} \;\; y \;\; \dot{y}]}$ when the target is in non-maneuvering phase and $\mathbf{X = [x \;\; \dot{x} \;\; \ddot{x} \;\; y \;\; \dot{y} \;\; \ddot{y}]}$ when the target is maneuvering. The process noise w and measurement noise v are assumed to be white and zero mean with covariance Q and R respectively.

Constant Velocity Model (Model1)

The 2^{nd} order kinematic model, with position and velocity components in each of the two Cartesian coordinates **x** and **y**. has the following transition and process noise gain matrices.

$$F = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$G = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & 0 \\ 0 & T^2/2 \\ 0 & T \\ 0 & 0 \end{bmatrix} \tag{27}$$

Note that the acceleration component in the above model, though identically equal to zero, has been retained for compatibility with the 3^{rd} order model to be discussed next. In eq. 27 the variations in velocity are modeled as zero-mean white noise accelerations. Low noise variance Q_1 is used with the model to represent the constant course and speed of the target in a non-maneuvering mode. The process noise intensity in each coordinate is generally assumed to be equal

$$\mathbf{Q_1} = \sigma_x^2 = \sigma_y^2 \tag{28}$$

Constant Acceleration Model (Model 2)

The 3^{rd} order model, with position, velocity and acceleration components in each of the two Cartesian coordinates **x** and **y**, has the following transition and process noise gain matrices.

$$F = \begin{bmatrix} 1 & T & T^2/2 & 0 & 0 & 0 \\ 0 & 1 & T & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & T^2/2 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$G = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 1 & 0 \\ 0 & T^2/2 \\ 0 & T \\ 0 & 1 \end{bmatrix} \tag{29}$$

The acceleration increments over a sampling period are a discrete time zero-mean white noise. A low value of process noise variance Q_2 (but relatively higher than Q_1) will yield nearly a constant acceleration motion. The noise variances in each coordinate are assumed to be equal

$$\mathbf{Q_2} = \sigma_x^2 = \sigma_y^2 \tag{30}$$

The following are the components of the target data simulation scenario :

a. Data Simulation for Single Sensor

- Number of targets = 2
- Target initial states -

Target 1 : $\mathbf{[\, x \;\; \dot{x} \;\; \ddot{x} \;\; y \;\; \dot{y} \;\; \ddot{y}\,] = [\, 0 \;\; 5 \;\; 0 \;\; 100 \;\; 5 \;\; 0 \,]}$

Target 2 : $\mathbf{[\,x\ \ \dot{x}\ \ \ddot{x}\ \ y\ \ \dot{y}\ \ \ddot{y}\,] = [\,1200\ \ 5\ \ 0\ \ -1200\ \ 5\ \ 0\,]}$

- Sampling time T = 1 sec
- False alarm density = 1.0e-005
- Measurement noise convariance R = 25
- Process noise covariance (for model 1) Q1 = 0.1
- Process noise covariance (for model 2) Q2=0.1
- Number of data points N=150
- Maneuvering injection time and magnitude of injection for two targets

Target No.	Maneuvering time (in sec.)		Maneuvering magnitude (m/sec 2)		
	Start	end	x-axis	y-axis	z-axis
1	30	50	1g	-1g	0
1	70	100	1g	-1g	0
2	50	80	-1g	1g	0

b. Data simulation for Multiple Sensors

- Number of sensors = 2
- Sensor locations -

Sensor 1 location : [0, 0, 0]
Sensor 2 location : [1000, 1000, 0]

- Number of targets = 3 sensor 1 and 3 for sensor 2
- Target initial states -

Target 1 : $\mathbf{[\,x\ \ \dot{x}\ \ \ddot{x}\ \ y\ \ \dot{y}\ \ \ddot{y}\,] = [\,0\ \ 5\ \ 0\ \ 100\ \ 5\ \ 0\,]}$
Target 2 : $\mathbf{[\,x\ \ \dot{x}\ \ \ddot{x}\ \ y\ \ \dot{y}\ \ \ddot{y}\,] = [\,1200\ \ 5\ \ 0\ \ -1200\ \ 5\ \ 0\,]}$
Target 3 : $\mathbf{[\,x\ \ \dot{x}\ \ \ddot{x}\ \ y\ \ \dot{y}\ \ \ddot{y}\,] = [\,1200\ \ 5\ \ 0\ \ -1200\ \ 5\ \ 0\,]}$
Target 4 : $\mathbf{[\,x\ \ \dot{x}\ \ \ddot{x}\ \ y\ \ \dot{y}\ \ \ddot{y}\,] = [\,1200\ \ 5\ \ 0\ \ -1200\ \ 5\ \ 0\,]}$

- Sampling time T = 1 sec
- False alarm density = 1.0e-007
- Measurement noise covariance R=5
- Process noise covariance (for model 1) Q1 = 0.01
- Process noise covariance (for model 2) Q2 = 0.01
- Number of data points N = 100
- Target 1 maneuvers with 1g acceleration from 40 to 50 sec while there is no acceleration in the other three targets

Results and Discussions

Single Sensor and Multiple Targets

The performance of the tracking filters are sensitive to the process noise covariance (Q) It is known that conventional Kalman filter with a constant velocity model can be used for tracking maneuvering targets if a higher value of Q is used during maneuver phase. However, during non-maneuver phase higher Q results in degraded performance. If a lower Q is used for tracking maneuvering targets, during maneuver phase there could be filter divergence and track loss due to the filter being unable to account for the maneuver. In order to bring out this, the sensitivity of the three association algorithms to the choice of Q values and models is evaluated by considering the following two combinations of models and Q values.

Table-1 : Combination of Q values for sensitivity study (IMMPDAF)		
Combinations	Q1	Q2
Case 1	Low	High
Case 2	Low	Low

The constant parameters used in each tracking algorithm are:

- Probability of detection $\mathbf{P}_D$ = 0.99
- Gate probability $\mathbf{P}_G$ = 0.99998
- Gate threshold **G** = 25
- Sojourn time τ = 15 seconds
- Onset model probability $\mathbf{P}_{12}$ = 0.12

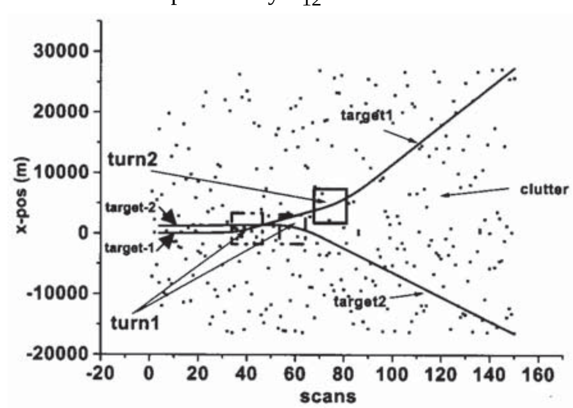

Fig. 3 True trjectories in clutter
(Target - 1 turns twice and target - 2 turn once)

Evaluation of IMMPDAF

Figure 3 shows the simulated x-position data of the two maneuvering targets in clutter. The performance of algorithm is tested under the two conditions of Q in terms of i) estimated and true x-position in clutter, ii) estimated standard deviations (σ_{x-pos}), and (iii) RSSPE defined by

$$\boldsymbol{RSSPE} = \sqrt{(x_t - \hat{x})^2 + (y_t - \hat{y})^2 \, (z_t - \hat{z})^2}$$

where $\mathbf{x}_t$, $\mathbf{y}_t$, $\mathbf{z}_t$ are the true target position and $\hat{\mathbf{x}}$, $\hat{\mathbf{y}}$, $\hat{\mathbf{z}}$ are the estimated target position.

For case 1, process noise covariance for model1 and model 2 is kept at 0.1 and 30 respectively whereas for case 2 process noise covariance values of 0.1 and 2 are used. Fig.4-5 show the performance comparison for case 1 and case 2 in terms of estimated and measured tracks with clutter, mode probability of tracks, σ_{x-pos} and RSSPE. It is clear that the tracking performance for both the combinations of Q are good. The mode probability clearly indicates the switching from the non-maneuver to the maneuver mode. The σ_{x-pos} shows a higher value during maneuver reflecting the correct situation (i.e. the filter is adaptively tracking the target which maneuvering). The results of case 2 show a delay in maneuver detection as compared to case 1 and also RSSPE is higher than that of case 1.

Fusion of Data from Multiple Sensors

Data of four targets seen by two sensors are fused using the IMMPDAF/case 1 algorithm. The data from each of the sensors are used to initiate tracks using the first two scans of measurements. The tracks are updated after measurement-to-track association with the valid measurements using IMMPDAF/case 1 algorithm. A state vector fusion algorithm is used to fuse the confirmed tracks after each scan. It is necessary to transform the data to a common reference point before fusion. Track-to-track association is used for combining similar tracks to avoid redundant tracks.

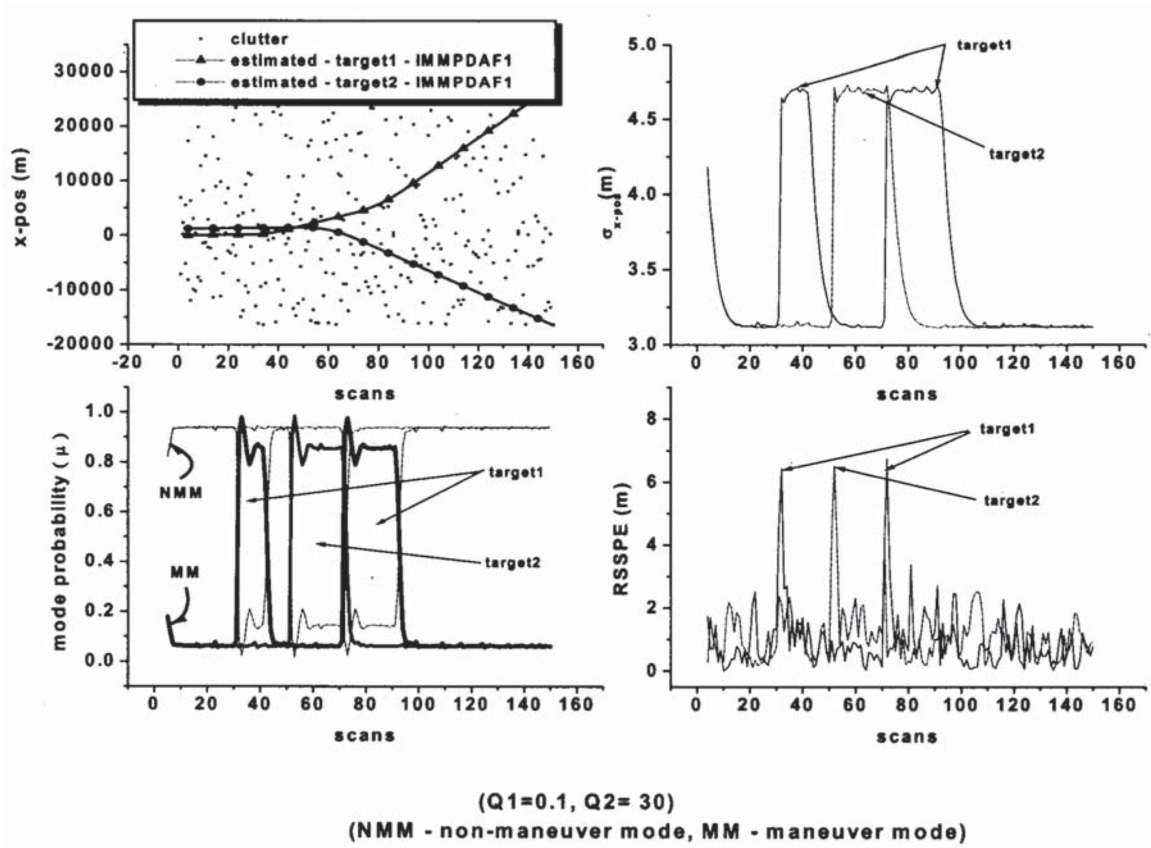

Fig. 4 Performance evaluation results - IMMPDAF (Case 1)

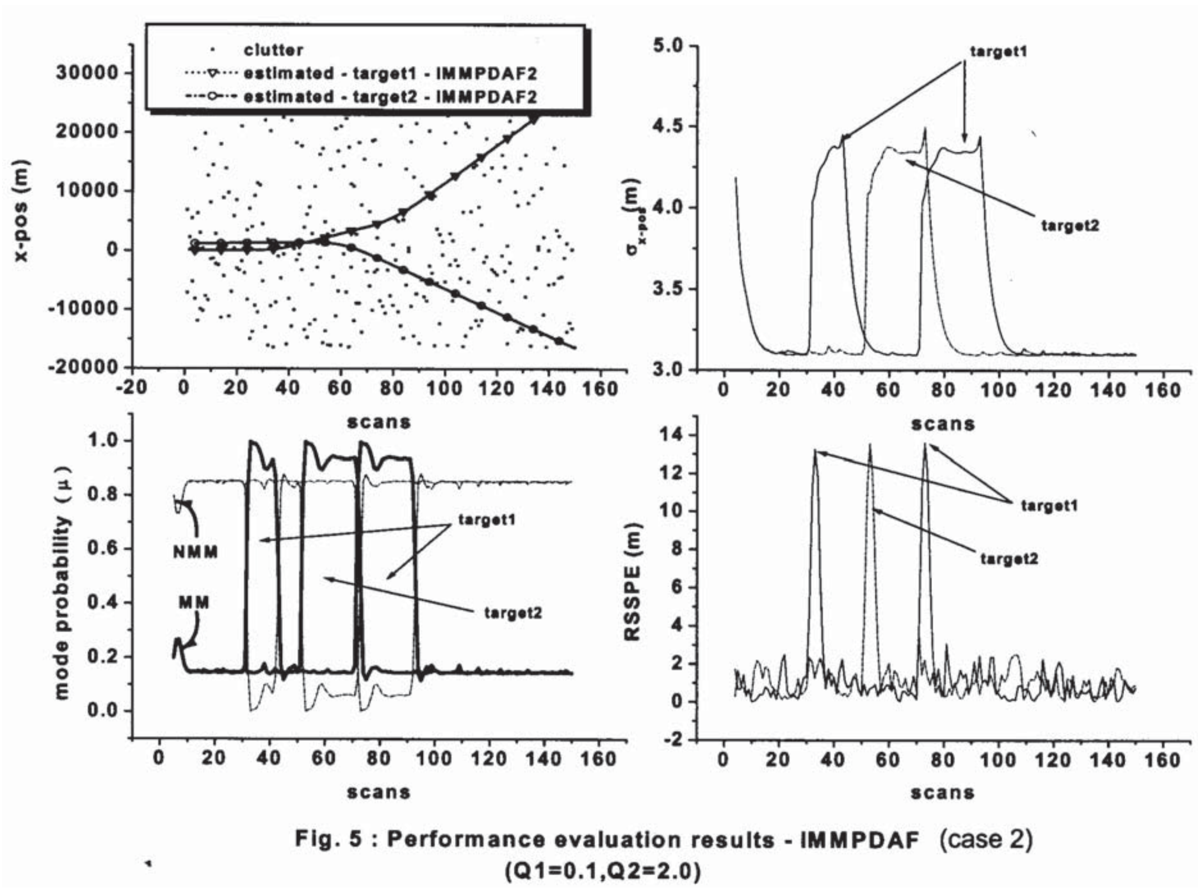

Fig. 5 Performance evaluation results - IMMPADF (Case 2)
(Q1=0.1, Q2=2.0)

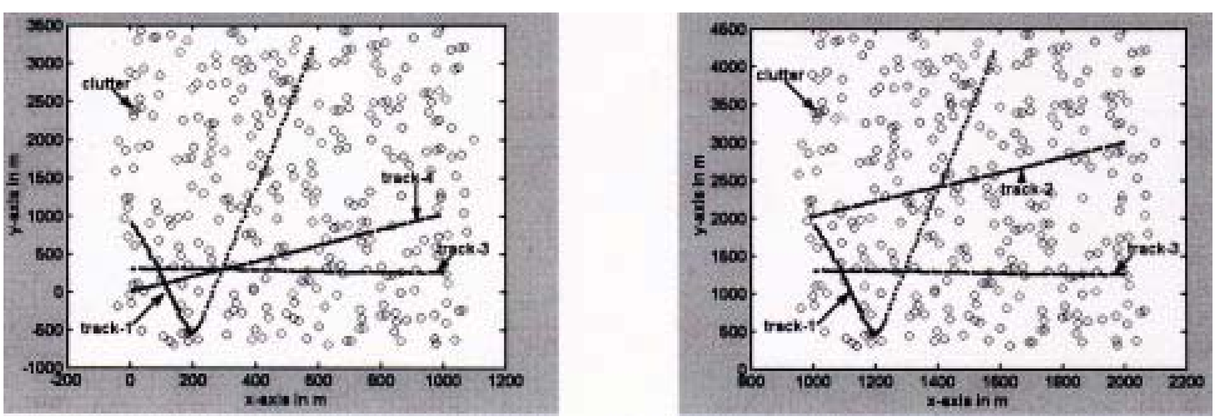

Fig. 6 Measurements from sensor -1 and sensor -2

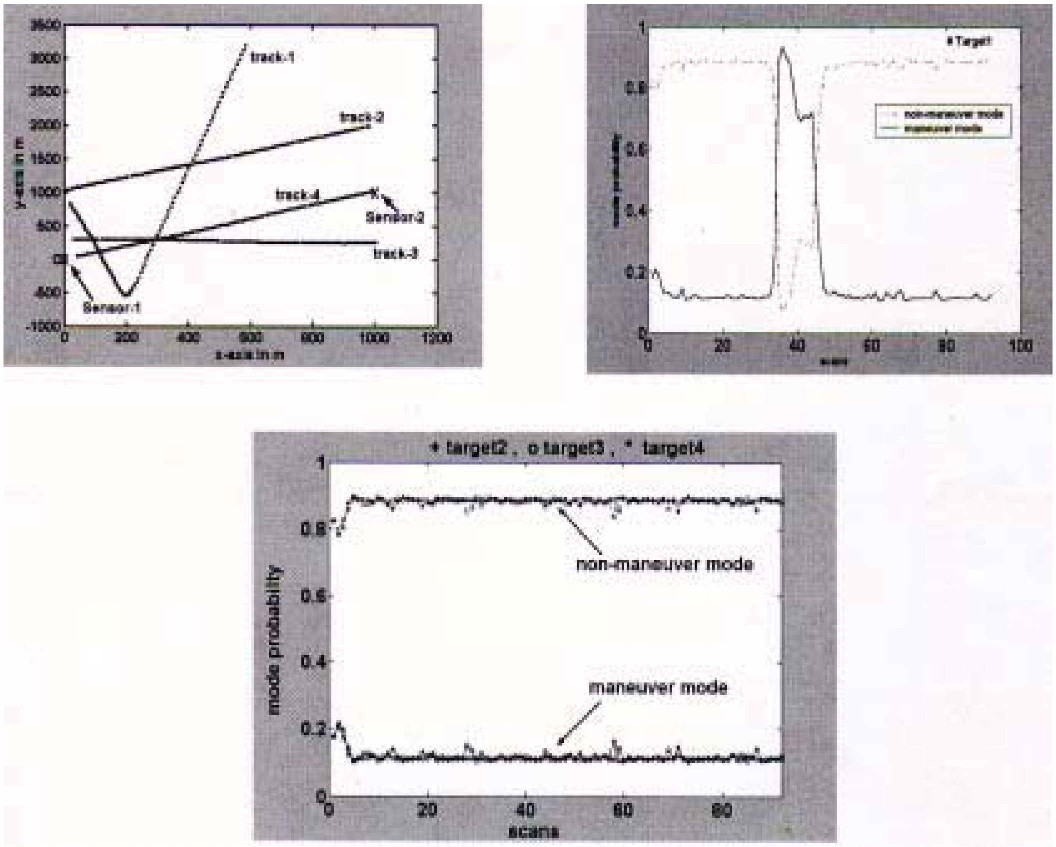

Fig. 7 Estimated/fused tracks and mode probability

In the present simulated scenario among four targets, three targets are seen by both the sensors. Fig.6 shows measurements for sensor1 and sensor 2. The estimated tracks and mode probability are shown in Fig.7. As expected, four targets are seen from the estimated positions after combining similar tracks using track-to-track fusion. From the mode probability of all tracks, it can be concluded that the event of target maneuvering is noticed in track-1 only.

Concluding Remarks

In this paper the performance of IMMPDAF for estimation of multiple maneuvering target trajectories in clutter has been evaluated. It is found that the IMMPDAF gives a realistic confidence in the estimates during maneuvers and lower RSSPE during the non-maneuvering phase of the targets. Sensitivity of the algorithm to the choice of the tracking models and process noise covariance values has also been evaluated. Results of fusion of data from two sensors using IMMPDAF have been presented.

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