

Parallel Detection Fusion for Multisensor Tracking of a Maneuvering Target in Clutter using IMMPDA Filtering

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Abstract

We present a (suboptimal) filtering algorithm for tracking a highly maneuvering target in a cluttered environment using multiple sensors. The filtering algorithm is developed by applying the basic Interacting Multiple Model (IMM) approach and the Probabilistic Data Association (PDA) technique to a two sensor (radar and infrared, for instance) problem for state estimation for the target. A detection fusion approach is followed where the raw sensor measurements are passed to a fusion node and fed directly to the target tracker. A multisensor probabilistic data association filter is developed for parallel sensor processing for target tracking under clutter. A past approach using parallel sensor processing has ignored certain data association probabilities leading to an erroneous derivation. Another existing approach applies only to non-maneuvering targets. The algorithm is illustrated via a highly maneuvering target tracking simulation example where two sensors, a radar and an infrared sensor, are used. Compared with an existing IMMPDA filtering algorithm with sequential sensor processing, the proposed algorithm achieves significant improvement in the accuracy of track estimation.

KEY WORDS: Multisensor Parallel Updating; Interacting Multiple Model (IMM); Probabilistic Data Association (PDA).

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1 Introduction

We consider the problem of tracking a single maneuvering target in clutter. This class of problem has received considerable attention in the literature [1, 6, 7, 8, 9, 12]. The switching multiple model approach has been found to be quite effective in modeling highly maneuvering targets [1, 2, 3, 4, 5, 6, 9]. In this approach various "modes" of target motion are represented by distinct kinematic models, and in a Bayesian framework, the target maneuvers are modeled by switching among these models controlled by a Markov chain. In the presence of clutter, the measurements at the sensors may not all have originated from the target-of-interest. In this case one has to solve the problem of data association. An effective approach in a Bayesian framework is that of probabilistic data association (PDA) [2, 12].

To accommodate the fact that the target can be highly maneuvering, we will follow a switching multiple model formulation as in [1, 2, 3, 4, 5, 6] and references therein. It is assumed that a track has been formed (initiated) and our objective is that of track maintenance. In [1] such a problem has been considered using multiple sensors, PDA, and switching multiple models. The optimal solution (in the minimum mean-square error sense) to target state estimation given sensor measurements and absence of clutter, requires exponentially increasing (with time) computational complexity; therefore, one has to resort to suboptimal approximations. For the switching multiple model approach, the interacting multiple model (IMM) algorithm of [4] has been found to offer a good compromise between the computational and storage requirements and estimation accuracy [3]. In the presence of clutter, one has to account for measurements of uncertain origin (target or clutter?). Here too, in a Bayesian framework, one has to resort to approximations to reduce the computational complexity, resulting in the PDA filter [1, 6, 8, 9, 12]. In [1] the IMM algorithm has been combined with the PDA filter in a multiple sensor scenario to propose a combined IMM/MSPDAF (interacting multiple model/ multisensor probabilistic data association filter) algorithm. The multisensor approach of [1] falls in the category of detection fusion where the raw measurements from all sensors are passed to a fusion node to be processed simultaneously [9]. Ref [1] uses sequential updating of the state estimates with measurements (i.e. updating the state estimates sequentially with measurements from different sensors). This results in computational savings but this approach is not necessarily the best. The other option is that of parallel updating (i.e. updating the state estimates with all the measurements at the same time as if they were from a single sensor). For linear systems, the two updating methods are algebraically equivalent but the parallel updating is computationally more expensive [6]. Ref [9] uses parallel updating but has some errors: during data association, all measurements at the same time from different sensors are assumed to be either from clutter or from the target. The possibility that a measurement from sensor 1 may be from target while the measurement from sensor 2 may be clutter-induced (and

vice-versa) in implicitly not allowed in [9] - this is clearly incorrect. Ref [13] allows for such distinctions (hypotheses), however, it is limited to non-maneuvering targets. In this paper, we extend the multisensor approach of [13] to maneuvering targets.

The paper is organized as follows. Section 2 presents the problem formulation. Section 3 describes the proposed IMM/MSPDAF algorithm with parallel detection fusion. Simulation results using the proposed algorithm for a realistic problem are given in Section 4. Finally, Section 5 presents a discussion of the results and some conclusions.

2 Problem Formulation

Assume that the target dynamics can be modeled by one of n hypothesis models. The model set is denoted as $\mathcal{M}_n := \{1, \dots, n\}$ and there are total q sensors from which q , or fewer (if probability of target detection is less than one) or more (due to clutter), measurement vectors are generated at a time. The event that model j is in effect during the sampling period $(t_{k-1}, t_k]$ is denoted by M_k^j . For the j -th hypothesized model (mode), the state dynamics and measurements, respectively, modeled as

$$x_k = F_{k-1}^j x_{k-1} + G_{k-1}^j v_{k-1}^j \quad (1)$$

and

$$z_k^l = h^{j,l}(x_k) + w_k^{j,l} \quad \text{for } l = 1, \dots, q \quad (2)$$

where x_k is the system state at t_k and of dimension n_x , z_k^l is the (true) measurement vector (i.e., due to the target) from sensor l at t_k and of dimension $n_{z,l}$, F_{k-1}^j and G_{k-1}^j are the system matrices when model j is in effect over the sampling period $(t_{k-1}, t_k]$, and $h^{j,l}$ is the nonlinear transformation of x_k to z_k^l ($l = 1, \dots, q$) for model j . Henceforth, time t_k will be denoted by k . A first-order linearized version of (2) is given by

$$z_k^l = H_k^{j,l} x_k + w_k^{j,l} \quad \text{for } l = 1, \dots, q \quad (3)$$

where $H_k^{j,l}$ is the Jacobian matrix of $h^{j,l}$ evaluated at some value of the estimate of state x_k . The process noise v_{k-1}^j and the measurement noise $w_k^{j,l}$ are mutually uncorrelated zero-mean white Gaussian processes with covariance matrices Q_{k-1}^j and $R_k^{j,l}$, respectively. At the initial time t_0 , the initial conditions for the system state under each model j are assumed to be Gaussian random variables with the known mean $\bar{x}_0^j$ and the known covariance P_0^j . The probability of model j at t_0 , $\mu_0^j = P\{M_0^j\}$, is also assumed to be known. The switching from model M_{k-1}^i to model M_k^j is governed by a finite-state stationary Markov chain with known transition probabilities $p_{ij} = P\{M_k^j | M_{k-1}^i\}$.

The following notations and definitions are used regarding the measurements at sensor l . Note that, in general, at any time k , some measurements may be due to clutter and some due to the target, i.e. there can be more than a single measurement at time k at sensor l . The measurement set (not yet validated) generated by sensor l at time k is denoted as

$$Z_k^l := \{z_k^{l(1)}, z_k^{l(2)}, \dots, z_k^{l(m_l)}\} \quad (4)$$

where m_l is the number of measurements generated by sensor l at time k . Variable $z_k^{l(i)}$ ($i = 1, \dots, m_l$) is the i th measurement within the set. The validated set of measurements of sensor l at time k will be denoted by Y_k^l , containing $\bar{m}_l$ ($\leq m_l$) measurement vectors. The cumulative set of validated measurements from sensor l up to time k is denoted as

$$Z^{k(l)} := \{Y_1^l, Y_2^l, \dots, Y_k^l\}. \quad (5)$$

The cumulative set of validated measurements from all sensors up to time k is denoted as

$$Z^k := \{Z^{k(1)}, Z^{k(2)}, \dots, Z^{k(q)}\} \quad (6)$$

where q is the number of sensors.

Our goal is to find the state estimate

$$\hat{x}_{k|k} := E\{x_k | Z^k\} \quad (7)$$

and the associated error covariance matrix

$$P_{k|k} := E\{(x_k - \hat{x}_{k|k})(x_k - \hat{x}_{k|k})' | Z^k\} \quad (8)$$

where x_k' denotes the transpose of x_k .

3 IMM/MSPDAF Algorithm for Parallel Detection Fusion

We now modify the IMM/PDA algorithms of [1] and [11] to derive the proposed IMM/MSPDAF with parallel detection fusion system. We confine our attention to the case of 2 sensors; however, the algorithm can be easily adapted to the case of arbitrary q sensors. We will only briefly outline the basic steps in "one cycle" (i.e., processing needed to update for a new set of measurements) of the IMM/MSPDA filter.

Assumed available: Given the state estimate $\hat{x}_{k-1|k-1}^j := E\{x_{k-1} | M_{k-1}^j, Z^{k-1}\}$, the associated covariance $P_{k-1|k-1}^j$, and the conditional mode probability $\mu_{k-1}^j := P[M_{k-1}^j | Z^{k-1}]$ at time $k-1$ for each mode $j \in \mathcal{M}_n$.

Step 1. Interaction – mixing of the estimate from the previous time ($\forall j \in \mathcal{M}_n$) :

predicted mode probability:

$$\mu_k^{j-} := P[M_k^j | Z^{k-1}] = \sum_i p_{ij} \mu_{k-1}^i. \quad (9)$$

mixing probability:

$$\mu^{i|j} := P[M_{k-1}^i | M_k^j, Z^{k-1}] = p_{ij} \mu_{k-1}^i / \mu_k^{j-}. \quad (10)$$

mixed estimate:

$$\hat{x}_{k-1|k-1}^{0j} := E\{x_{k-1} | M_k^j, Z^{k-1}\} = \sum_i \hat{x}_{k-1|k-1}^i \mu^{i|j}. \quad (11)$$

covariance of the mixed estimate:

$$\begin{aligned} P_{k-1|k-1}^{0j} &:= E\{[x_{k-1} - \hat{x}_{k-1|k-1}^{0j}][x_{k-1} - \hat{x}_{k-1|k-1}^{0j}]' | M_k^j, Z^{k-1}\} \\ &= \sum_i \{P_{k-1|k-1}^i + [\hat{x}_{k-1|k-1}^i - \hat{x}_{k-1|k-1}^{0j}][\hat{x}_{k-1|k-1}^i - \hat{x}_{k-1|k-1}^{0j}]' \} \mu^{i|j}. \end{aligned} \quad (12)$$

Step 2. Predicted state and measurements for sensors 1 and 2 ($\forall j \in \mathcal{M}_n$) :

state prediction:

$$\hat{x}_{k|k-1}^j := E\{x_k | M_k^j, Z^{k-1}\} := F_{k-1}^j \hat{x}_{k-1|k-1}^{0j}. \quad (13)$$

state prediction error covariance:

$$\begin{aligned} P_{k|k-1}^j &:= E\{[x_k - \hat{x}_{k|k-1}^j][x_k - \hat{x}_{k|k-1}^j]' | M_k^j, Z^{k-1}\} \\ &= F_{k-1}^j P_{k-1|k-1}^{0j} F_{k-1}^{j'} + G_{k-1}^j Q_{k-1}^j G_{k-1}^{j'}. \end{aligned} \quad (14)$$

The mode-conditioned predicted measurement for sensor l is

$$\hat{z}_k^{j,l} := h^{j,l}(\hat{x}_{k|k-1}^j). \quad (15)$$

Using the linearized version (3), the covariance of the mode-conditioned residual

$$\nu_k^{j,l(i)} := z_k^{l(i)} - \hat{z}_k^{j,l},$$

is given by (assume $q=2$, the case of 2 sensors)

$$S_k^{j,1} := E\{\nu_k^{j,1(i)} \nu_k^{j,1(i)'} | M_k^j, Z^{k-1}\} := H_k^{j,1} P_{k|k-1}^j H_k^{j,1'} + R_k^{j,1}, \quad (16)$$

$$S_k^{j,2} := E\{\nu_k^{j,2(i)} \nu_k^{j,2(i)'} | M_k^j, Z^{k-1}\} := H_k^{j,2} P_{k|k-1}^j H_k^{j,2'} + R_k^{j,2} \quad (17)$$

where $H_k^{j,l}$ is the first order derivative (Jacobian matrix) of $h^{j,l}(\cdot)$ evaluated at the state prediction $\hat{x}_{k|k-1}^j$ (see (15)). Note that (16) and (17) assume that $z_k^{l(i)}$ originates from the target. The results (16) and (17) do not depend upon the actual measurements.

As mentioned earlier, since our approach to the problem deals with multiple simultaneous measurements [13, 14] arising from two separate sensors that are tracking a single target through a common surveillance region, a method for fusion of multiple measurements has to be devised. In order to do this, now the combined covariance S_k^j of the mode-conditioned residual obtained from (16) and (17) also needs to be considered as follows:

$$S_k^j := \begin{bmatrix} H_k^{j,1} \\ H_k^{j,2} \end{bmatrix} P_{k|k-1}^j \begin{bmatrix} H_k^{j,1'} & H_k^{j,2'} \end{bmatrix} + \begin{bmatrix} R_k^{j,1} & 0 \\ 0 & R_k^{j,2} \end{bmatrix} \quad (18)$$

Step 3. Measurement validation for sensors 1 and 2 ($\forall j \in \mathcal{M}_n$):

There is uncertainty regarding the measurements' origins. Therefore, we perform validation for each target separately. One sets up a validation gate for sensor l centered at the mode-conditioned predicted measurement, $\hat{z}_k^{j,l}$. Let $(|A| = \det(A))$

$$j_a := \arg \left\{ \max_{j \in \mathcal{M}_n} |S_k^{j,l}| \right\}.$$

Then measurement $z_k^{l(i)}$ ($i=1,2,\dots,m_l$) is validated if and only if

$$[z_k^{l(i)} - \hat{z}_k^{j_a,l}]' [S_k^{j_a,l}]^{-1} [z_k^{l(i)} - \hat{z}_k^{j_a,l}] < \gamma \quad (19)$$

where γ is an appropriate threshold. The volume of the validation region with the threshold γ is

$$V_k^l := c_{n_{zl}} \gamma^{n_{zl}/2} |S_k^{j_a,l}|^{1/2} \quad (20)$$

where n_{zl} is the dimension of the measurement and $c_{n_{zl}}$ is the volume of the unit hypersphere of this dimension ($c_1 = 2$, $c_2 = \pi$, $c_3 = 4\pi/3$, etc.). Choice of γ is discussed in more detail in ([6], Sec. 2.3.2). After performing the validation for each target separately, we deal with all the validated data for the measurement fusion.

Step 4. State estimation with validated measurement from sensors 1 and 2 ($\forall j \in \mathcal{M}_n$):

From among all the raw measurements from sensor l at time k , i.e. $Z_k^l := \{z_k^{l(1)}, z_k^{l(2)}, \dots, z_k^{l(m_l)}\}$, define the set of validated measurement for sensor l at time k as

$$Y_k^l := \{y_k^{l(1)}, y_k^{l(2)}, \dots, y_k^{l(\bar{m}_l)}\} \quad (21)$$

where $\bar{m}_l$ is total number of validated measurement for sensor l at time k and

$$y_k^{l(i)} := z_k^{l(i)} \quad (22)$$

where $1 \leq l_1 < l_2 < \dots < l_{\bar{m}_l} \leq m_l$ when $\bar{m}_l \neq 0$. Define the association events (hypotheses) $\theta_k^{a,b}$ as follows (here we follow [?])

- $\theta_k^{0,0}$: none of the measurements in Y_k^1 or Y_k^2 is target originated.
- $\theta_k^{0,b}$: only $y_k^{2(b)}$ in Y_k^2 is a target measurement, all other measurements in Y_k^1 or Y_k^2 are clutter, $a = 0, b = 1, \dots, \bar{m}_2$.
- $\theta_k^{a,0}$: only $y_k^{1(a)}$ in Y_k^1 is a target measurement, all other measurements in Y_k^1 or Y_k^2 are clutter, $a = 1, \dots, \bar{m}_1, b = 0$.
- $\theta_k^{a,b}$: $y_k^{1(a)}$ and $y_k^{2(b)}$ in Y_k^1 and Y_k^2 , respectively, are target measurements, all other measurements are clutter, $a = 1, \dots, \bar{m}_1, b = 1, \dots, \bar{m}_2$.

Therefore, there are a total of $\bar{m}_1\bar{m}_2 + \bar{m}_1 + \bar{m}_2 + 1$ possible association hypotheses, each of which has an association probability. Define the mode-conditioned association event probabilities as

$$\beta_k^{j,a,b} := P\{\theta_k^{a,b} | M_k^j, Y_k^1, Y_k^2, Z^{k-1}\}. \quad (23)$$

Exploiting the diffuse model for clutter in [1, 6], it turns out that

$$\begin{aligned} \beta_k^{j,0,0} &= C \frac{(1-P_{D_1}P_{G_1})(1-P_{D_2}P_{G_2})}{(V_k^1)^{\bar{m}_1}(V_k^2)^{\bar{m}_2}}, \quad a = 0, b = 0 \\ \beta_k^{j,0,b} &= C \frac{P_{D_2}(1-P_{D_1}P_{G_1})N[\nu_k^{j,2(b)}; 0, S_k^{j,2}]}{(V_k^2)^{\bar{m}_2-1}\bar{m}_2}, \quad a = 0, b = 1, \dots, \bar{m}_2 \\ \beta_k^{j,a,0} &= C \frac{P_{D_1}(1-P_{D_2}P_{G_2})N[\nu_k^{j,1(a)}; 0, S_k^{j,1}]}{(V_k^1)^{\bar{m}_1-1}\bar{m}_1}, \quad a = 1, \dots, \bar{m}_1, b = 0 \\ \beta_k^{j,a,b} &= C \frac{N[\nu_k^{j,1(a)}; 0, S_k^{j,1}]N[\nu_k^{j,2(b)}; 0, S_k^{j,2}]P_{D_1}P_{D_2}}{\bar{m}_1\bar{m}_2(V_k^1)^{\bar{m}_1-1}(V_k^2)^{\bar{m}_2-1}}, \quad a = 1, \dots, \bar{m}_1, b = 1, \dots, \bar{m}_2 \end{aligned} \quad (24)$$

where P_{D_1} and P_{D_2} are the detection probabilities that the sensors 1 and 2 detect the target, respectively, P_{G_1} and P_{G_2} are probabilities the target is in the validation region observed from sensors 1 and 2, respectively, C is a normalization constant such that $\sum_{a=0}^{\bar{m}_1} \sum_{b=0}^{\bar{m}_2} \beta_k^{j,a,b} = 1 \forall j$ and

$$N[x; y, P] := |2\pi P|^{-1/2} \exp \left[-\frac{1}{2} (x - y)' P^{-1} (x - y) \right].$$

Define the mode-conditioned innovations $\nu_k^{j,a,b}$ as

$$\begin{aligned}
\nu_k^{j,0,0} &= \begin{bmatrix} 0_{n_{z1} \times 1} \\ 0_{n_{z2} \times 1} \end{bmatrix}, \quad a = 0, b = 0 \\
\nu_k^{j,0,b} &= \begin{bmatrix} 0_{n_{z1} \times 1} \\ \nu_k^{j,2(b)} \end{bmatrix}, \quad a = 0, b = 1, \dots, \bar{m}_2 \\
\nu_k^{j,i,0} &= \begin{bmatrix} \nu_k^{j,1(a)} \\ 0_{n_{z2} \times 1} \end{bmatrix}, \quad a = 1, \dots, \bar{m}_1, b = 0 \\
\nu_k^{j,a,b} &= \begin{bmatrix} \nu_k^{j,1(a)} \\ \nu_k^{j,2(b)} \end{bmatrix}, \quad a = 1, \dots, \bar{m}_1, b = 1, \dots, \bar{m}_2.
\end{aligned} \tag{25}$$

The likelihood function for each mode m is

$$\Lambda_k^j := p[Y_k^1, Y_k^2 | M_k^j, Z^{k-1}] = \sum_{a=0}^{\bar{m}_1} \sum_{b=0}^{\bar{m}_2} p[Y_k^1, Y_k^2, \theta_k^{a,b} | M_k^j, Z^{k-1}] \tag{26}$$

where

$$\begin{aligned}
p[Y_k^1, Y_k^2, \theta_k^{a,b} | M_k^j, Z^{k-1}] &= p[Y_k^1, Y_k^2 | M_k^j, \theta_k^{a,b}, Z^{k-1}] P[\theta_k^{a,b}] \\
&= \begin{cases} \frac{(1-P_{D1}P_{G1})(1-P_{D2}P_{G2})}{[V_k^1]^{\bar{m}_1}[V_k^2]^{\bar{m}_2}}, & a = 0, b = 0 \\ \frac{(1-P_{D1}P_{G1})(P_{D2}P_{G2})/\bar{m}_2}{P_{G2}[V_k^2]^{\bar{m}_2-1}} \times N[\nu_k^{j,2(b)}; 0, S_k^{j,2}], & a = 0, b = 1, \dots, \bar{m}_2 \\ \frac{(P_{D1}P_{G1})(1-P_{D2}P_{G2})/\bar{m}_1}{P_{G1}[V_k^1]^{\bar{m}_1-1}} \times N[\nu_k^{j,1(a)}; 0, S_k^{j,1}], & a = 1, \dots, \bar{m}_1, b = 0 \\ \frac{(P_{D1}P_{G1})(P_{D2}P_{G2})/(\bar{m}_1\bar{m}_2)}{P_{G1}[V_k^1]^{\bar{m}_1-1}P_{G2}[V_k^2]^{\bar{m}_2-1}} \times N[\nu_k^{j,a,b}; 0, S_k^j], & a = 1, \dots, \bar{m}_1, b = 1, \dots, \bar{m}_2. \end{cases} \tag{27}
\end{aligned}$$

Using $\hat{x}_{k|k-1}^j$ (from (13)) and its covariance $P_{k|k-1}^j$ (from (14)), one computes the partial update $\hat{x}_{k|k}^j$ and its covariance $P_{k|k}^j$ according to the standard PDAF [1], except that the augmented state is conditioned on $\theta_k^{a,b}$ with data fusion from sensors 1 and 2. Define the combined mode-conditioned innovations

$$\nu_k^j := \sum_{a=0}^{\bar{m}_1} \sum_{\substack{b=0 \\ a+b \neq 0}}^{\bar{m}_2} \beta_k^{j,a,b} \nu_k^{j,a,b} \tag{28}$$

Therefore, partial update of the state estimate

$$\hat{x}_{k|k}^{j,a,b} := E\{x_k | \theta_k^{a,b}, M_k^j, Z^{k-1}, Y_k^1, Y_k^2\} = \hat{x}_{k|k-1}^j + W_k^{j,a,b} \nu_k^{j,a,b} \tag{29}$$

where Kalman gains, $W_k^{j,a,b}$, are computed as

$$= \begin{cases} W_k^{j,0,0} = 0, & \text{for } a = 0, b = 0 \\ W_k^{j,a,0} = P_{k|k-1}^j [\tilde{H}_k^{j,1'} [S_k^{j,1}]^{-1} \ 0], & \text{for } a \neq 0, b = 0 \\ W_k^{j,0,b} = P_{k|k-1}^j [0 \ \tilde{H}_k^{j,2'} [S_k^{j,2}]^{-1}], & \text{for } a = 0, b \neq 0 \\ W_k^{j,a,b} = P_{k|k-1}^j \tilde{H}_k^{j'} [S_k^j]^{-1}, & \text{for } a \neq 0, b \neq 0, \end{cases} \quad (30)$$

where $H_k^{j'} = [H_k^{j,1'} \ H_k^{j,2'}]$. Therefore, the mode-conditioned update of the state estimate

$$\hat{x}_{k|k}^j := E \{x_k | M_k^j, Z^{k-1}, Y_k^1, Y_k^1\} = \sum_{a=0}^{\tilde{m}_1} \sum_{\substack{b=0 \\ a+b \neq 0}}^{\tilde{m}_2} \beta_k^{j,a,b} \hat{x}_{k|k-1}^{j,a,b} \quad (31)$$

and the covariance of $\hat{x}_{k|k}^j$

$$P_{k|k}^j := P_{k|k-1}^j - \sum_{\substack{a=0 \\ a+b \neq 0}}^{\tilde{m}_1} \sum_{\substack{b=0 \\ a+b \neq 0}}^{\tilde{m}_2} \beta_k^{j,a,b} W_k^{j,a,b} S_k^{j,a,b} W_k^{j,a,b'} + \sum_{\substack{a=0 \\ a+b \neq 0}}^{\tilde{m}_1} \sum_{\substack{b=0 \\ a+b \neq 0}}^{\tilde{m}_2} \beta_k^{j,a,b} W_k^{j,a,b} \nu_k^{j,a,b} \nu_k^{j,a,b'} W_k^{j,a,b'} \\ - \left[\sum_{\substack{a=0 \\ a+b \neq 0}}^{\tilde{m}_1} \sum_{\substack{b=0 \\ a+b \neq 0}}^{\tilde{m}_2} \beta_k^{j,a,b} W_k^{j,a,b} \nu_k^{j,a,b} \right] \left[\sum_{\substack{a=0 \\ a+b \neq 0}}^{\tilde{m}_1} \sum_{\substack{b=0 \\ a+b \neq 0}}^{\tilde{m}_2} \beta_k^{j,a,b} W_k^{j,a,b} \nu_k^{j,a,b} \right]'. \quad (32)$$

Step 5. Update of mode probabilities ($\forall m \in M^n$) :

$$\mu_k^j := P [M_k^j | Z^k] = \frac{1}{C} \mu_k^{j-} \Lambda_k^j \quad (33)$$

where C is a normalization constant such that $\sum_j \mu_k^j = 1$.

Step 6. Combination of the mode-conditioned estimates ($\forall m \in M^n$) :

The final augmented state estimate update at time k is given by

$$\hat{x}_{k|k} = \sum_j \hat{x}_{k|k}^j \mu_k^j \quad (34)$$

and its covariance is given by

$$P_{k|k} = \sum_j \left\{ P_{k|k}^j + [\hat{x}_{k|k}^j - \hat{x}_{k|k}] [\hat{x}_{k|k}^j - \hat{x}_{k|k}]' \right\} \mu_k^j. \quad (35)$$

4 Simulation Example

The following example of tracking a highly maneuvering target in clutter is considered.

The True Trajectory: The target starts at location [21689 10840 40] in Cartesian coordinates in meters. The initial velocity (in m/s) is [-8.3 -399.9 0] and the target stays at constant altitude with a constant speed of 400 m/s . Its trajectory is:

- a straight line with constant velocity between 0 and 20s,
- a coordinated turn (0.15 rad/s) with constant acceleration of 60 m/s² between 20 and 35s,
- a straight line with constant velocity between 35 and 55s,
- a coordinated turn (0.1 rad/s) with constant acceleration of 40 m/s² between 55 and 70s,
- a straight line with constant velocity between 70 and 90s.

The Target Motion Models: These are exactly as in [11]. In each mode the target dynamics are modelled in Cartesian coordinates as $x_k = Fx_{k-1} + Gv_{k-1}^j$ where the state of the target is position, velocity, acceleration, and process noise in each of the 3 Cartesian coordinates (x , y , and z). Model 1 for Nearly constant velocity model with zero mean perturbation in acceleration; Model 2 for Wiener process acceleration (nearly constant acceleration motion); Model 3 for Wiener process acceleration (model with large acceleration increments, for the onset and termination of maneuvers). The details regarding these models may be found in [11]. The initial model probabilities are $\mu_0^1 = 0.8$, $\mu_0^2 = 0.1$ and $\mu_0^3 = 0.1$. The mode switching probability matrix for two targets is also identical and is as in [1] Fig. 1 shows the true trajectory of the target.

The Sensors: Two sensors (we assume time synchronization of observations, etc., but not collocation) are used to obtain the measurements. The measurements from sensor l for model j are $z_k^l = h^{j,l}(x_k) + w_k^{j,l}$ for $l = 1$ and 2, reflecting range and azimuth angle for sensor 1 (radar) and azimuth and elevation angles for sensor 2 (infrared). The range, azimuth, and elevation angle transformations would be given by $r_l = \{(x - x_l)^2 + (y - y_l)^2 + (z - z_l)^2\}^{1/2}$, $a_l = \tan^{-1}[(y - y_l)/(x - x_l)]$, $e_l = \tan^{-1}[(z - z_l)/\{(x - x_l)^2 + (y - y_l)^2\}^{1/2}]$, respectively, if the sensor l were located at $[x_l \ y_l \ z_l]$. In our simulations, we placed the radar at $[-4000 \ 4000 \ 0]$ m and the infrared sensor at $[5000 \ 0 \ 0]$ m. The measurement noise $w_k^{j,l}$ for sensor l is assumed to be zero-mean white Gaussian with known covariances, $R^1 = \text{diag}[q_r, q_{a1}] = \text{diag}[400\text{m}^2, 49\text{mrad}^2]$ with q_r and q_{a1} denoting the variances for the radar range and azimuth measurement noises, respectively, and $R^2 = \text{diag}[q_{a2}, q_e] = \text{diag}[4\text{mrad}^2, 4\text{mrad}^2]$ with q_{a2} and q_e denoting the variances for the infrared sensor azimuth and elevation measurement noises, respectively. The sampling interval was $T=1$ s and it was assumed that the probability of detection $P_d=0.997$ for both sensors.

The Clutter: For generating false measurements in simulations, the clutter was assumed to be Poisson distributed with expected number of $\lambda_1 = 50 \times 10^{-6}/\text{m mrad}$ for sensor 1 and $\lambda_2 = 3.5 \times 10^{-4}/\text{m}^2 \text{ mrad}$ for sensor 2. These statistics were used for generating the clutter in all simulations. However, a nonparametric clutter model was used for implementing all the algorithms for target tracking.

Other Parameters: The gates for setting up the validation regions for both the sensors were based on the threshold $\gamma=16$ corresponding to a gate probability $P_G=0.9997$.

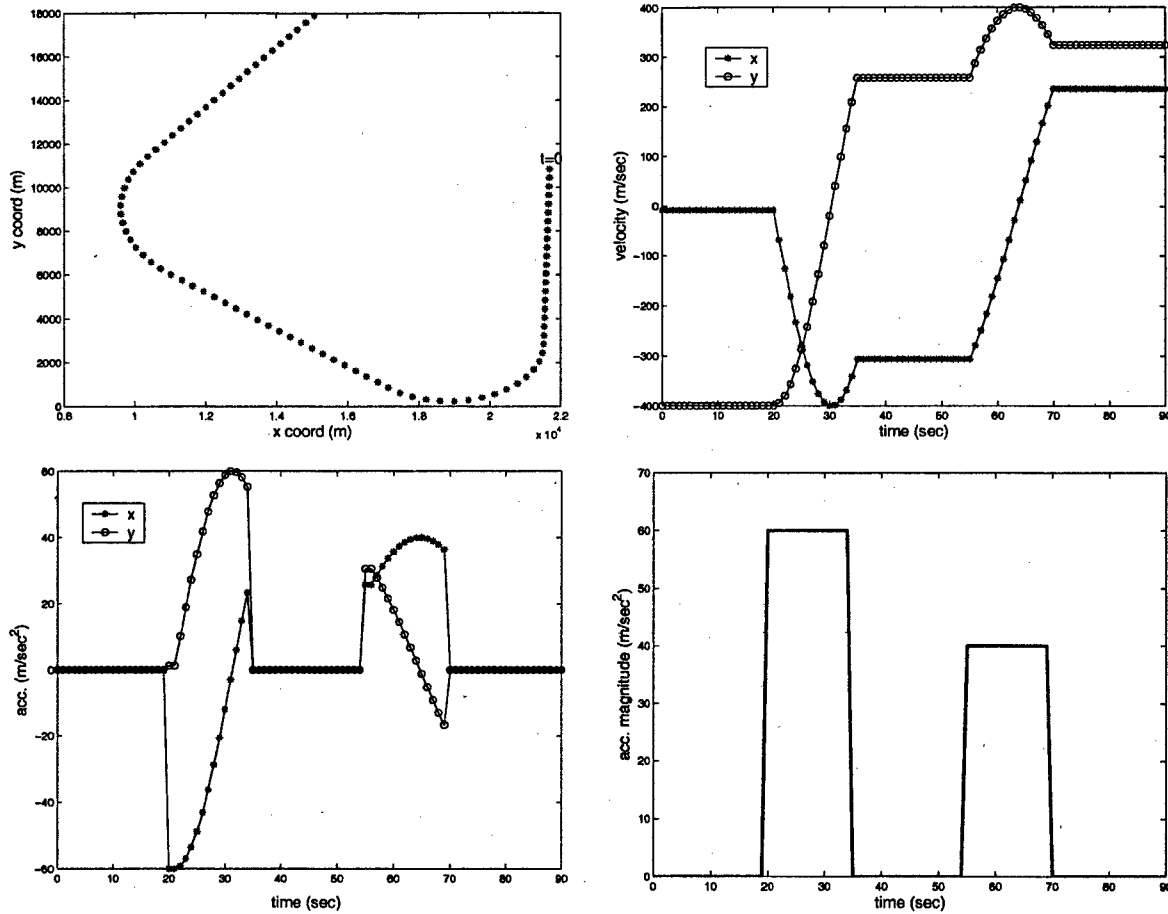


Figure 1: True trajectory of maneuvering target (read left to right, top to bottom): (a) Position in xy plane; (b) x and y velocities; (c) x and y accelerations; (d) magnitude of acceleration.

Simulation Results: The results were obtained from 100 Monte Carlo runs. Fig. 2 shows the results of proposed IMM/MSPDAF based on 100 runs comparing with the standard sequential IMM/MSPDAF in terms of the RMSE (root mean-square error) in position. It is seen that parallel updating can significantly improve the accuracy of track estimation. In addition, it is also seen that tracking with separated sensors can improve the accuracy of track estimation compared to using collocated sensors.

5 Conclusions

We investigated an IMM/MSPDAF algorithm with parallel detection fusion for tracking a highly maneuvering target in clutter. The proposed algorithm was illustrated via a simulation example where it outperformed the IMM/MSPDAF algorithm with sequential updating [1].

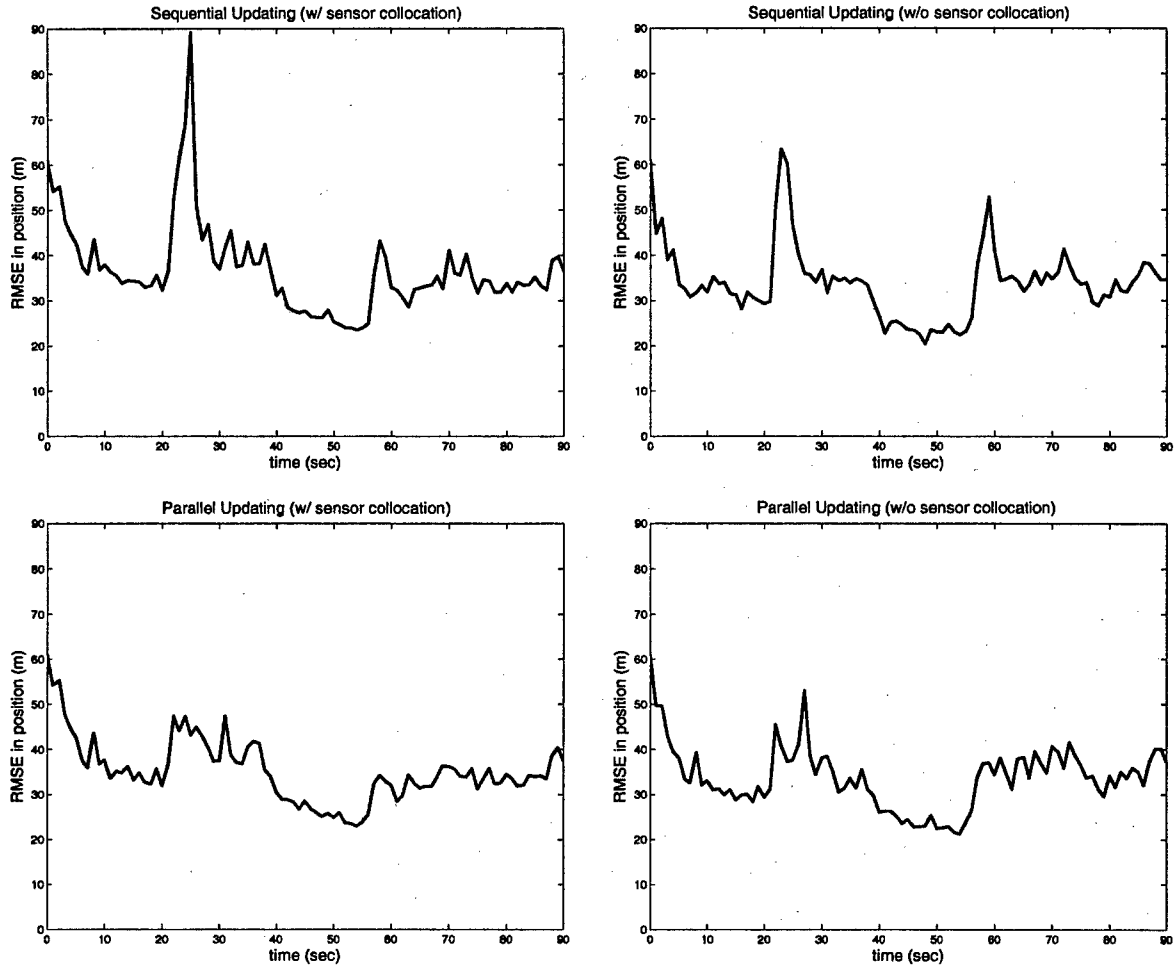


Figure 2: Performance comparison between the proposed parallel detection fusion IMM/MSPDAF and sequential updating IMM/MSPDAF of [1] (read left to right, top to bottom): (a) sequential updating [1] with colocated sensors, (b) sequential updating [1] with separated sensors, (c) proposed parallel detection fusion with colocated sensors, (d) proposed parallel detection fusion with separated sensors.

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