

Multi-Sensor Distributed Fusion Based on Integrated Probabilistic Data Association

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Abstract—This paper presents two multi-sensor fusion algorithms for single target tracking in cluttered environments. We establish a track quality measure for fusion tracks in centralized fusion and track-to-track fusion. The fusion algorithms are derived by extending the integrated probabilistic data association (IPDA) technique to multi-sensor systems. We propose a centralized fusion algorithm called the Multi-Sensor IPDA (MS-IPDA). The Multi-Sensor Distributed track-to-track Fusion IPDA (MSDF-IPDA) filter algorithm is also proposed for distributed sensor systems. Both algorithms recursively update the probability of target existence which may be used for false track discrimination.

Keywords—Multi-Sensor, Distributed Track Fusion, Integrated Probabilistic Data Association (IPDA), Track Existence, Centralized Fusion

I. INTRODUCTION

This paper presents two single target tracking algorithms that determine the target existence probabilities of fusion tracks in cluttered environments. One is a centralized fusion, and the other is a track-to-track fusion. A majority of algorithms for single-sensor target tracking in clutter are based on the all-neighbor probabilistic data association (PDA) [1-4, 9]. Single sensor target tracking algorithms are being extended to find the estimation solutions for multiple sensor systems.

The PDA is extended to multi-sensor PDA (MSPDA) in [10-12] where the parallel or the sequential [13] updating schemes are used. For tracking a maneuvering target in the presence of clutter with multiple sensors, the PDA is combined with the interactive multiple model (IMM) [6] filter called sequential multi-sensor IMM/PDA (S-IMM/MSPDA) that is suggested in [7] where the sequential filtering of [13] is applied for fusing the information of multiple sensors. This algorithm is later adapted to a parallel updating scheme and is denoted as IMM/MSPDA [8].

These approaches to single target tracking have a common assumption that every track is true, i.e. follows a target. In other words, the probability of target existence (PTE) is 1 so that PTE is not used as a track quality

measure for false track discrimination. The usage of PTE as a track quality measure is proposed in the integrated probabilistic data association (IPDA) in [3, 4], which is combined with the IMM filter (IMMIPDA) [9] for maneuvering target tracking. For multi-target tracking in clutter, the extension to multi-target tracking, Joint PDA (JPDA)[16] and integrated PDA (JIPDA) with track existence probability [15] are proposed. To alleviate computational load of the multi-target data association algorithms, linear multi-target IPDA (LM-IPDA) [5] and iterative JIPDA (iJIPDA) [19] are proposed based on single sensors. These algorithms may be applied in a sequential form to handle each sensor measurement separately for centralized fusion or they may be applied to each sensor to generate tracks for distributed track-to-track fusion. For track fusion in multiple sensor systems, track information from each sensor and association between the tracks are needed. Various track fusion algorithms such as convex fusion, Bar-Shalom-Campo rules, tracklet fusion, and track association metrics [20-22] have been developed for distributed tracking situations. These approaches are based on the assumptions that associations between tracks are perfect and there is no false track so that track quality measure is not needed. It may not be possible to satisfy the assumptions in real applications. In this paper, the confirmed tracks regardless of false and true nature of the tracks generated by each sensor are transmitted to a fusion center with track information including the PTE.

The goal of the paper is to develop multi-sensor IPDA (MS-IPDA) for centralized fusion systems and multi-sensor Distributed track-to-track Fusion IPDA (MSDF-IPDA) for distributed fusion systems.

The paper is organized as follows. Section II presents the problem formulation. The MS-IPDA algorithm is described in Section III. Section IV presents the MSDF-IPDA algorithm followed by a simulation example in Section V, followed by concluding remarks VI.

II. PROBLEM STATEMENT

We assume that the target dynamics are modeled in

Cartesian coordinate by

$$x_{k+1} = F \cdot x_k + v_k, \quad x_k \in R^{n_x} \quad (1)$$

where x_k is the target state vector at time k , F is the transition matrix and v_k is a zero-mean, white Gaussian noise sequence with known variance Q_k .

Similar to other target tracking algorithms, the point target assumption is used. Each target τ may create zero or one target measurement per sensor per scan according to probability of detection P_D . The target measurement for the s -th sensor is denoted as

$$y_k^s = H_s \cdot x_k + w_k^s \quad (2)$$

where w_k^s is a sample of zero-mean white Gaussian noise sequence with covariance R^s . Clutter measurements are random and follow a Poisson distribution [1]. A Poisson process is characterized by the clutter measurement density.

Denote by z_k^s , the set of m_s measurements received by the s -th sensor at a current scan. Let $z_{k,i}^s$ denote the i -th measurement of z_k^s . If the target measurement y_k^s is present, $y_k^s \in z_k^s$.

By denoting the measurement set of sensor s collected up to the scan time k as

$$Z_s^k = \{z_k^s, Z_s^{k-1}\}, \quad (3)$$

then the cumulative set of all measurements from N sensors collected up to time k is given by

$$\begin{aligned} Z^k &= \{Z_1^k, Z_2^k, \dots, Z_N^k\} \\ &= \{z_k^1, z_k^2, \dots, z_k^N, Z^{k-1}\}. \end{aligned} \quad (4)$$

The event that the target exists at time k is denoted by χ_k . Then the probability that the target exists at time k is $P(\chi_k)$, and the probability that the target does not exist is

$$P(\bar{\chi}_k) = 1 - P(\chi_k). \quad (5)$$

The objective is to recursively calculate the posterior probability density function (pdf) from

$$p(x_k, \chi_k | Z^k) = p(x_k | \chi_k, Z^k) P(\chi_k | Z^k), \quad (6)$$

where the state estimate and its error covariance under the condition of target existence for the multi-sensor system are obtained from

$$x_{k|k} = \int x_k p(x_k | \chi_k, Z^k) dx_k, \quad (7)$$

$$P_{k|k} = \int (x_k - x_{k|k})(x_k - x_{k|k})^T p(x_k | \chi_k, Z^k) dx_k. \quad (8)$$

The PTE $P(\chi_k | Z^k)$ is obtained by a recursive formula.

III. MULTI-SENSOR IPDA (MS-IPDA)

We present the MS-IPDA algorithm for the system with two sensors by modifying the existing single sensor based IPDA (SS-IPDA) in [3]. This approach corresponds to a centralized fusion scheme in which all measurements are used simultaneously. The MS-IPDA equations can be easily adapted to the case of N sensors since the form of the results is analogous to the SS-IPDA.

A. State Estimate and Error Covariance Matrix

The state estimate for the two-sensor system is

$$\begin{aligned} x_{k|k} &= \int x_k p(x_k | Z_1^k, Z_2^k) dx_k \\ &= \sum_{i_1=0}^{m_1} \sum_{i_2=0}^{m_2} \int x_k p(x_k | \chi_{k,i_1}^1, \chi_{k,i_2}^2, \chi_k, Z^k) dx_k \beta_{i_1,i_2} \\ &= \sum_{i_1=0}^{m_1} \sum_{i_2=0}^{m_2} x_{k|k}^{i_1,i_2} \beta_{i_1,i_2} \end{aligned} \quad (9)$$

where χ_{k,i_s} is the hypothesis that the i_s -th measurement of the sensor s is the target measurement (if i_s is 0, it means there is no sensor s target detection), and all others are clutter measurements, $x_{k|k}^{i_1,i_2}$ is the state estimate for each measurement set from both sensors as in [8], and β_{i_1,i_2} , the data association probability representing the weight for each measurement set, is defined as

$$\beta_{i_1,i_2} = P(\chi_{k,i_1}^1, \chi_{k,i_2}^2 | \chi_k, Z^k). \quad (10)$$

The updated state estimate $x_{k|k}^{i_1,i_2}$ and its error covariance $P_{k|k}^{i_1,i_2}$ are obtained by the Kalman filter algorithm with the predicted state estimate $x_{k|k-1}$ and its error covariance $P_{k|k-1}$ such as

$$x_{k|k}^{i_1,i_2} = x_{k|k-1} + K_k^{i_1,i_2} (z_k^{i_1,i_2} - H^{i_1,i_2} x_{k|k-1}) \quad (11)$$

$$P_{k|k}^{i_1,i_2} = (I - K_k^{i_1,i_2} H^{i_1,i_2}) P_{k|k-1} \quad (12)$$

where the stacked measurement $z_k^{i_1,i_2}$ satisfies

$$z_k^{i_1,i_2} = \begin{cases} (z_{k,i_1}^1, z_{k,i_2}^2)^T, & \text{for } i_1 \neq 0, i_2 \neq 0 \\ (z_{k,i_1}^1, 0_{n_2 \times 1}^T)^T, & \text{for } i_1 \neq 0, i_2 = 0 \\ (0_{n_1 \times 1}^T, z_{k,i_2}^2)^T, & \text{for } i_1 = 0, i_2 \neq 0 \\ (0_{n_1 \times 1}^T, 0_{n_2 \times 1}^T)^T, & \text{for } i_1 = 0, i_2 = 0 \end{cases} \quad (13)$$

and where the measurement matrix H^{i_1,i_2} depends on target detection outcomes such as

$$H^{i_1, i_2} = \begin{cases} (H_1^T, H_2^T)^T, & \text{for } i_1 \neq 0, i_2 \neq 0 \\ (H_1^T, 0_{n_2 \times 1}^T)^T, & \text{for } i_1 \neq 0, i_2 = 0 \\ (0_{n_1 \times n_x}^T, H_2^T)^T, & \text{for } i_1 = 0, i_2 \neq 0 \\ (0_{n_1 \times n_x}^T, 0_{n_2 \times n_x}^T)^T, & \text{for } i_1 = 0, i_2 = 0 \end{cases} \quad (14)$$

In the equation above, the subscript $m \times n$ implies an $m \times n$ matrix.

The error covariance matrix of $x_{k|k}$ in (15) equals

$$P_{k|k} = \sum_{i_1=0}^{m_1} \sum_{i_2=0}^{m_2} (P_{k|k}^{i_1, i_2} + x_{k|k}^{i_1, i_2} \cdot x_{k|k}^{i_1, i_2 T}) \beta_{i_1, i_2} - x_{k|k} (x_{k|k})^T \quad (15)$$

B. The Data Association Probabilities

The data association probabilities for the two-sensor system at time k under the condition of target existence are obtained as

$$\begin{aligned} \beta_{0,0} &= \frac{(1 - P_D^1 P_G^1)(1 - P_D^2 P_G^2)}{\mu_k^{1,2}}, i_1 = i_2 = 0 \\ \beta_{i_1,0} &= \frac{P_D^1 p(z_{k,i_1}^1) / \lambda_k^1 (1 - P_D^2 P_G^2)}{\mu_k^{1,2}}, i_1 \neq 0, i_2 = 0 \\ \beta_{0,i_2} &= \frac{(1 - P_D^1 P_G^1) P_D^2 p(z_{k,i_2}^2) / \lambda_k^2}{\mu_k^{1,2}}, i_1 = 0, i_2 \neq 0 \\ \beta_{i_1, i_2} &= \frac{P_D^1 P_D^2 p(z_{k,i_1}^1, z_{k,i_2}^2) / (\lambda_k^1 \lambda_k^2)}{\mu_k^{1,2}}, i_1 \neq 0, i_2 \neq 0 \end{aligned} \quad (16)$$

where P_D^s is the detection probability of the target for the sensor s , P_G^s is the gating probability, λ_k^s is the clutter density, and $\mu_k^{1,2}$ is a normalizing constant given by

$$\begin{aligned} \mu_k^{1,2} &= (1 - P_D^1 P_G^1)(1 - P_D^2 P_G^2) \\ &+ P_D^1 (1 - P_D^2 P_G^2) \sum_{i_1=1}^{m_1} p(z_{k,i_1}^1) / \lambda_k^1 \\ &+ (1 - P_D^1 P_G^1) P_D^2 \sum_{i_2=1}^{m_2} p(z_{k,i_2}^2) / \lambda_k^2 \\ &+ P_D^1 P_D^2 \sum_{i_1=1}^{m_1} \sum_{i_2=1}^{m_2} p(z_{k,i_1}^1, z_{k,i_2}^2) / (\lambda_k^1 \lambda_k^2). \end{aligned} \quad (17)$$

We consider 2 cases when calculating the measurement likelihoods. In the single measurement case,

$$p(z_{k,i_s}^s) = N(z_{k,i_s}^s; H_s x_{k|k-1}, S_s), s = 1, 2 \quad (18)$$

where the covariance is written as

$$S_s = H_s P_{k|k-1} H_s^T + R_s. \quad (19)$$

In the two-measurement case,

$$\begin{aligned} p(z_{k,i_1}^1, z_{k,i_2}^2) &= p(z_{k,i_1}^1, z_{k,i_2}^2 | Z^{k-1}) \\ &= N\left(\begin{bmatrix} z_{k,i_1}^1 \\ z_{k,i_2}^2 \end{bmatrix}; H x_{k|k-1}, S\right) \end{aligned} \quad (20)$$

where $H = (H_1^T, H_2^T)^T$ and the covariance S is written as

$$S = H P_{k|k-1} H^T + R$$

(21)

Note that $R = \text{diag}(R^1, R^2)$.

Due to the joint Gaussian pdf for the joint measurement case, the association probability β_{i_1, i_2} is not the product of association probability calculated independently for each sensor measurement. In [10], an approximation that the data association probability equals the product of each data association probability of the sensors is used.

C. Probability of Track Existence

The update of the probability of track existence consists of two steps.

The propagation step is the same as the SS-IPDA propagation. For the Markov Chain I [3], the a priori probability of track existence at time k is calculated by

$$P(\chi_k | Z^{k-1}) = \pi_{11} P(\chi_{k-1} | Z^{k-1}) + \pi_{21} P(\bar{\chi}_{k-1} | Z^{k-1}) \quad (22)$$

where the components of the Markov Chain transition matrix are

$$\pi_{11} = P(\chi_k | \chi_{k-1}), \quad \pi_{21} = P(\chi_k | \bar{\chi}_{k-1}). \quad (23)$$

The second step is a update step given measurements at time k . The posterior probability of track existence at time k is calculated by

$$P(\chi_k | Z^k) = \frac{\mu_k^{1,2}}{1 - (1 - \mu_k^{1,2}) P(\chi_k | Z^{k-1})} P(\chi_k | Z^{k-1}) \quad (24)$$

IV. MULTI-SENSOR DISTRIBUTED TRACK-TO-TRACK FUSION IPDA (MSDF-IPDA)

Here we extend the MS-IPDA algorithm to Multi-Sensor Distributed track-to-track Fusion IPDA (MSDF-IPDA). The MS-IPDA processes measurement sets from two sensors. The MSDF-IPDA processes confirmed local IPDA tracks received from the individual sensors. The benefits of this approach are that it can be applied for track fusion application in the distributed sensor system in cluttered environments and enhance the false track discrimination performance. We consider the following track fusion situation.

Each sensor transmits confirmed tracks to a fusion center and the MSDF-IPDA algorithm is used to fusing the tracks.

Initially there are no tracks in the fusion center and the initial tracks are generated from the confirmed tracks transmitted from each sensor. The confirmed local tracks include both true and false tracks. Each SS-IPDA initiates and updates tracks from measurements of each sensor, and it confirms the tracks reaching the confirmation threshold of the PTE or terminates the tracks with low PTE, which is called false track discrimination. This configuration is depicted in Fig. 1.

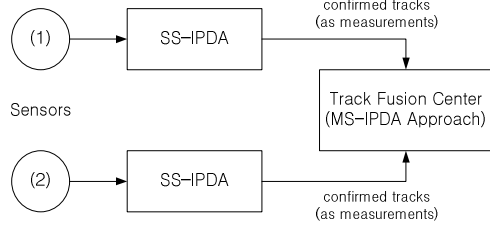


Fig.1. MSDF-IPDA

We assume that the two sensors cover the identical surveillance area and transmit the local tracks at the same instant.

Let η_1 , η_2 and τ denote tracks of sensor 1 and sensor 2 and the track fusion track, and $\{\eta_1\}$, $\{\eta_2\}$ and $\{\tau\}$ the set of tracks of sensor (1) and sensor (2) and the fusion center, respectively. The posteriori probability density functions of the state for each track η_1 , η_2 and the priori probability density function for track τ assuming track existence are

$$P(x_k^{\eta_1} | \chi_k^{\eta_1}, Z_1^k) = N(x_k^{\eta_1}; x_{k|k}^{\eta_1}, P_{k|k}^{\eta_1}) \quad (25)$$

$$, P(x_k^{\eta_2} | \chi_k^{\eta_2}, Z_2^k) = N(x_k^{\eta_2}; x_{k|k}^{\eta_2}, P_{k|k}^{\eta_2}) \quad (26)$$

$$\text{and } P(x_k^\tau | \chi_k^\tau, Z^{k-1}) = N(x_k^\tau; x_{k|k-1}^\tau, P_{k|k-1}^\tau). \quad (27)$$

The track sets of $\{\eta_1\}$ and $\{\eta_2\}$ assume the role of measurement set of track τ . The tracks η_1 and η_2 are obtained with the track detection probabilities P_T^1 and P_T^2 . For track fusion, the likelihood of track η_s with respect to track τ is

$$\begin{aligned} p_\tau^{\eta_s} &\equiv E(x_{k|k}^{\eta_s} | Z_s^k) \\ &= \int_{x_k^\tau} p(x_{k|k}^{\eta_s} | x_k^\tau) p(x_k^\tau | Z_s^k) dx_k^\tau \end{aligned} \quad (28)$$

where the subscript s denotes the s -th sensor and the likelihood function satisfies

$$p(x_k^{\eta_s} | x_k^\tau) = N(x_k^{\eta_s}; H_\tau^{\eta_s} x_k^\tau, P_k^{\eta_s}) \quad (29)$$

where $H_\tau^{\eta_s}$ is the measurement matrix mapping from the state space of track η_s to the space of track τ and it is the identical matrix due to the identical coordinate.

The likelihood function is

$$p_\tau^{\eta_s} = N(x_{k|k}^{\eta_s}; x_{k|k-1}^\tau, S_\tau^{\eta_s}) \quad (30)$$

where the track innovation covariance is obtained similar to (34) as

$$S_\tau^{\eta_s} = P_{k|k}^{\eta_s} + P_{k|k-1}^\tau - P_{k|k}^{\eta_s, \tau} - (P_{k|k}^{\eta_s, \tau})^T \quad (31)$$

where the cross covariance between the tracks is defined as

$$P_{k|k}^{\eta_s, \tau} = E((x_{k|k}^{\eta_s} - x_k)(x_{k|k-1}^\tau - x_k)^T) \quad (32)$$

In the MSDF-IPDA approach to the track fusion, the state estimate and error covariance matrix are computed through fusing the tracks η_1 and η_2 with τ by the correlated Kaman filter update equation and track association probability $\beta_\tau^{\eta_1, \eta_2}$.

The track association probability is

$$\begin{aligned} \beta_\tau^{\eta_1, \eta_2} &= P(\chi_\tau^{\eta_1}, \chi_\tau^{\eta_2} | \chi_k^\tau, Z^k) \\ &= \frac{1}{L_k^{1,2}} \begin{cases} (1 - P_T^1)(1 - P_T^2), & \eta_1 = \eta_2 = 0 \\ P_T^1(1 - P_T^2) \psi_k^{\eta_1} p_\tau^{\eta_1} / \lambda_{\eta_1}, & \eta_1 > 0, \eta_2 = 0 \\ (1 - P_T^1) P_T^2 \psi_k^{\eta_2} p_\tau^{\eta_2} / \lambda_{\eta_2}, & \eta_1 = 0, \eta_2 > 0 \\ P_T^1 P_T^2 \psi_k^{\eta_1} p_\tau^{\eta_1} / \lambda_{\eta_1} \psi_k^{\eta_2} p_\tau^{\eta_2} / \lambda_{\eta_2}, & \eta_1 > 0, \eta_2 > 0 \end{cases} \end{aligned} \quad (33)$$

where $\chi_\tau^{\eta_s}$ is a possible track association event that each of the track set $\{\eta_s\}$ follows the target (χ_τ^0 means that none of the track set $\{\eta_s\}$ follows the target), P_T^s is the track detection probability, λ_{η_s} is the clutter density, $\psi_k^{\eta_s} (\equiv P(\chi_k^{\eta_s} | Z_s^k))$ is the PTE of η_s . For the joint measurement case, the likelihood function for $\eta_1 > 0$ and $\eta_2 > 0$ is considered as the product of two independent likelihood functions of each sensor for simplicity and easy implementation.

$L_k^{1,2}$ equals

$$\begin{aligned} L_k^{1,2} &= (1 - P_T^1)(1 - P_T^2) \\ &\quad + P_T^1(1 - P_T^2) \sum_{\eta_1 > 0}^{\{\eta_1\}} \psi_k^{\eta_1} p_\tau^{\eta_1} / \lambda_{\eta_1} \\ &\quad + (1 - P_T^1) P_T^2 \sum_{\eta_2 > 0}^{\{\eta_2\}} \psi_k^{\eta_2} p_\tau^{\eta_2} / \lambda_{\eta_2} \\ &\quad + P_T^1 P_T^2 \sum_{\eta_1 > 0}^{\{\eta_1\}} \sum_{\eta_2 > 0}^{\{\eta_2\}} (\psi_k^{\eta_1} p_\tau^{\eta_1} / \lambda_{\eta_1}) (\psi_k^{\eta_2} p_\tau^{\eta_2} / \lambda_{\eta_2}). \end{aligned} \quad (34)$$

The PTE for the fusion track is updated with the equation

$$\psi_{k|k}^\tau = \frac{L_k^{1,2} \psi_{k|k-1}^\tau}{1 - (1 - L_k^{1,2}) \psi_{k|k-1}^\tau} \quad (35)$$

where $\psi_{k|k-1}^\tau (\equiv P(\chi_k^\tau | Z^{k-1}))$ is the predicted PTE of fusion track τ as in (26).

The state estimate and the error covariance matrix are updated as follows. The fusion center calculates, there are track state $x_{k-1|k-1}^\tau$ and its covariance estimate $P_{k-1|k-1}^\tau$ at $k-1$. The state estimate and the error covariance estimate are predicted to k .

Each track $x_{k|k-1}^\tau$ is fused with one track η_s of track set $\{\eta_s\}$ by the correlated Kalman filter update for $(\eta_1 > 0 \text{ and } \eta_2 = 0)$ or $(\eta_1 = 0 \text{ and } \eta_2 > 0)$ by

$$x_{k|k}^{\eta_s|\tau} = x_{k|k-1}^\tau + K_\tau^{\eta_s} (x_{k|k}^{\eta_s} - x_{k|k-1}^\tau) \quad (36)$$

where the Kalman gain $K_\tau^{\eta_s}$ equals $K_\tau^{\eta_s} = (P_{k|k-1}^\tau - P_{k|k}^{\eta_s, \tau})(S_\tau^{\eta_s})^{-1}$, with $S_\tau^{\eta_s}$ defined in (48). If η_s is zero, $x_{k|k}^{\eta_s|\tau} = x_{k|k-1}^\tau$. For $(\eta_1 > 0 \text{ and } \eta_2 > 0)$, the track fusion is executed sequentially, in other words, the track state $x_{k|k}^{\eta_2|\tau}$ is used to update $x_{k|k-1}^\tau$ to generate $x_{k|k}^{\eta_2|\tau}$ first, and $x_{k|k}^{\eta_1}$ is used to update $x_{k|k}^{\eta_2|\tau}$ to generate $x_{k|k}^{(\eta_1, \eta_2)|\tau}$ by

$$x_{k|k}^{(\eta_1, \eta_2)|\tau} = x_{k|k}^{\eta_2|\tau} + K_{\eta_2|\tau}^{\eta_1} (x_{k|k}^{\eta_1} - x_{k|k}^{\eta_2|\tau}) \quad (37)$$

where the Kalman gain $K_{\eta_2|\tau}^{\eta_1}$ is defined by

$$K_{\eta_2|\tau}^{\eta_1} = (P_{k|k}^{\eta_1} - P_{k|k}^{\eta_1, \eta_2, \tau})(S_{\eta_2|\tau}^{\eta_1})^{-1} \quad (38)$$

and $S_{\eta_2|\tau}^{\eta_1}$ is

$$S_{\eta_2|\tau}^{\eta_1} = P_{k|k}^{\eta_1} + P_{k|k}^{\eta_2|\tau} - P_{k|k}^{\eta_1, \eta_2, \tau} - (P_{k|k}^{\eta_1, \eta_2, \tau})^T \quad (39)$$

where the cross covariance between tracks $x_{k|k}^{\eta_1}$ and $x_{k|k}^{\eta_2|\tau}$ is defined by

$$P_{k|k}^{\eta_1, \eta_2, \tau} = E\{(x_{k|k}^{\eta_1} - x_k)(x_{k|k}^{\eta_2|\tau} - x_k)^T\}. \quad (40)$$

We know that the track state $x_{k|k}^{(\eta_1, 0)|\tau}$ is equivalent to the track state $x_{k|k}^{\eta_1|\tau}$ and the error covariance $P_{k|k}^{(\eta_1, 0)|\tau}$ is equivalent to the error covariance $P_{k|k}^{\eta_1|\tau}$.

The final fused state estimate for the track set with the track association probabilities is

$$x_{k|k}^\tau = \sum_{\eta_1=0}^{\{\eta_1\}} \sum_{\eta_2=0}^{\{\eta_2\}} \beta_\tau^{\eta_1, \eta_2} x_{k|k}^{(\eta_1, \eta_2)|\tau}. \quad (41)$$

The final fused covariance matrix equals

$$P_{k|k}^\tau = \sum_{\eta_1=0}^{\{\eta_1\}} \sum_{\eta_2=0}^{\{\eta_2\}} \beta_\tau^{\eta_1, \eta_2} (P_{k|k}^{(\eta_1, \eta_2)|\tau} + x_{k|k}^{(\eta_1, \eta_2)|\tau} (x_{k|k}^{(\eta_1, \eta_2)|\tau})^T - x_{k|k}^\tau (x_{k|k}^\tau)^T) \quad (42)$$

where the error covariance matrix $P_{k|k}^{(\eta_1, \eta_2)|\tau}$ for the state $x_{k|k}^{(\eta_1, \eta_2)|\tau}$ is defined by

$$P_{k|k}^{(\eta_1, \eta_2)|\tau} = (I - K_{\eta_2|\tau}^{\eta_1}) P_{k|k}^{\eta_2|\tau} (I - K_{\eta_2|\tau}^{\eta_1})^T + K_{\eta_2|\tau}^{\eta_1} P_{k|k}^{\eta_1} (K_{\eta_2|\tau}^{\eta_1})^T + (I - K_{\eta_2|\tau}^{\eta_1}) P_{k|k}^{\eta_1, \eta_2, \tau} (K_{\eta_2|\tau}^{\eta_1})^T + K_{\eta_2|\tau}^{\eta_1} (P_{k|k}^{\eta_1, \eta_2, \tau})^T (I - K_{\eta_2|\tau}^{\eta_1})^T \quad (43)$$

and the error covariance matrix $P_{k|k}^{\eta_s|\tau}$ for the state $x_{k|k}^{\eta_s|\tau}$ of (36) equals

$$P_{k|k}^{\eta_s|\tau} = (I - K_\tau^{\eta_s}) P_{k|k}^\tau (I - K_\tau^{\eta_s})^T + K_\tau^{\eta_s} P_{k|k}^{\eta_s} (K_\tau^{\eta_s})^T + (I - K_\tau^{\eta_s}) P_{k|k}^{\eta_s, \tau} (K_\tau^{\eta_s})^T + K_\tau^{\eta_s} (P_{k|k}^{\eta_s, \tau})^T (I - K_\tau^{\eta_s})^T \quad (44)$$

This finishes the MSDF-IPDA recursion cycle at k .

V. SIMULATION EXAMPLE

Simulation compares the two-sensor based MS-IPDA algorithm with the single-sensor based IPDA and MSDF-IPDA algorithms in regard to track confirmation and false track discrimination performance with various probabilities of target detection in a cluttered environment. The MS-IPDA is an optimal centralized fusion methodology in which both sensor 1 and sensor 2 transmit all the measurements to a fusion center and tracks are initialized and updated by feasible combinations of the measurements from the sensors. This centralized fusion approach may not be practical for many real multi-sensor systems due to the excessive communication burden and/or system interface requirements. However, it can be used as a performance bound.

Both sensors cover a two-dimensional surveillance region 1000m long and 400m wide and each sensor observes the whole region with the scan time of $T = 1 \text{ sec}$. The clutter measurements follow a uniform Poisson distribution with the clutter measurement density $10^{-4} / \text{scan} / m^2$ for both sensors. One target moves uniformly for 50 seconds, in other words, 50 scans. The target starts at location $[200 \text{ m}, 50 \text{ m}]$ and its initial velocity is $[15 \text{ m/s}, 0 \text{ m/s}]$. The target dynamic model follows (1). The state x_k consists of position and velocity in 2 coordinates (x and y) with the transition matrix

$$F = \begin{bmatrix} F(T) & 0 \\ 0 & F(T) \end{bmatrix}, \quad F(T) = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \quad (45)$$

where T is the sampling period. The process noise is zero-mean white Gaussian noise sequence with known variance

$$Q = q \begin{bmatrix} Q(T) & 0 \\ 0 & Q(T) \end{bmatrix}, \quad Q(T) = \begin{bmatrix} T^4/4 & T^3/2 \\ T^3/2 & T^2 \end{bmatrix} \quad (46)$$

where $q = 0.866 \text{ m}^2 / \text{s}^4$.

The stacked measurement matrix is

$$H = \begin{bmatrix} H_1 \\ H_2 \end{bmatrix}, \quad H_1 = H_2 = [1 \ 0 \ 1 \ 0] \quad (47)$$

with the sensor measurement matrices H_1 and H_2 for the two sensors 1 and 2 respectively. The measurement error covariance matrix R is

$$R = \begin{bmatrix} R^1 & 0 \\ 0 & R^2 \end{bmatrix}, \quad R^1 = R^2 = \begin{bmatrix} 25 & 0 \\ 0 & 25 \end{bmatrix} m^2. \quad (48)$$

The Markov Chain I target existence propagation model is

$$[\pi_{11} \ \pi_{12}] = [0.98 \ 0]. \quad (49)$$

The simulation experiments consist of 300 Monte Carlo runs for high and low detection probability (P_D) situations. For the high detection probability case, $P_D = 0.8$, while $P_D = 0.6$ for the low detection probability case. The tracks are initiated using one-point initialization [23] and initial PTE is assigned to each track. The tracks are confirmed if the PTE exceeds the confirmation threshold and are eliminated if the PTE falls below the termination threshold. Each simulation experiment consists of 300 simulation runs (15,000 scans per each sensor).

The false track discrimination results are shown in Fig.2 for $P_D = 0.8$ and Fig.3 for $P_D = 0.6$. Each graph shows the number of confirmed true track (nCTT) and confirmation rate of true track at every single scan.

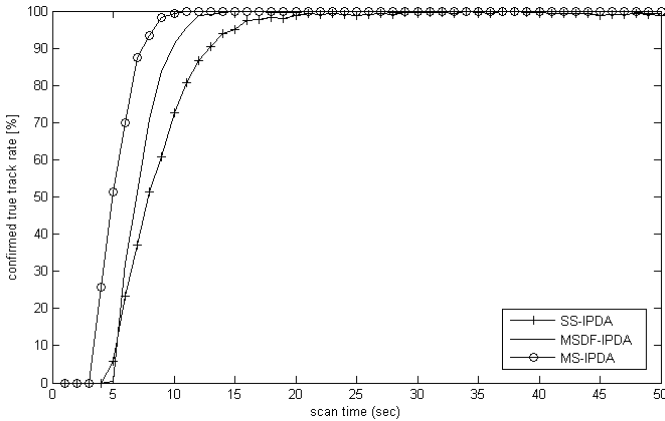


Fig.2. Confirmed True Track Rate ($P_D = 0.8$)

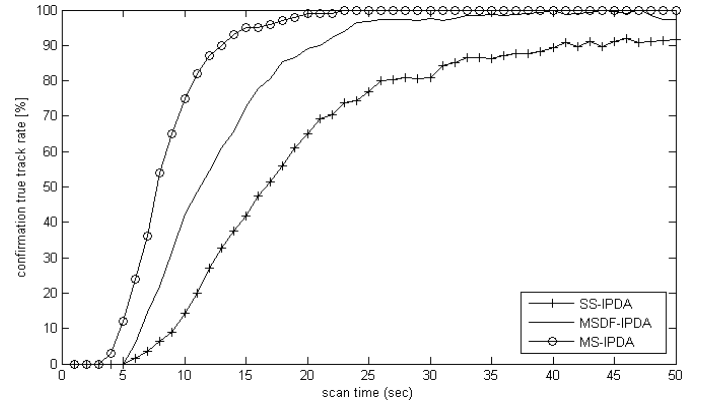


Fig.3. Confirmed True Track Rate ($P_D = 0.6$)

The quantitative statistical outcomes at the 50th scan are summarized as follows.

- (a) nCTT to follow their original targets and to maintain more than 25 scans.
- (b) nCTT with track maintenance period less than 25 scans.

The nCTT(Total) is summation of (a) and (b). The nCTT Rate is the percentage of nCTT(Total) for 300 targets. The number of confirmed false track scans (nCFTScans) is the summation of the existing periods for all confirmed false tracks in scans, which include the tracks which survive to the 50th scan and the tracks terminated before the 50th scan. The computation load is evaluated by estimating the average time of each simulation for 300 Monte Carlo runs and its average running time in seconds through Matlab 7 programming on a 2.5 GHz Intel PC running window XP is presented in the TABLE I and II as shown.

TABLE I Confirmed True Track Performance Comparison (PD=0.8)			
items	SS-IPDA	MSDF-IPDA	MS-IPDA
(a)	290	298	298
(b)	7	0	2
nCTT(Total)	297	298	300
nCTT Rate	99.00	99.33	100.00
nCFTScans	98	99	95
time(sec/run)	2.53	5.39	7.17

TABLE II Confirmed True Track Performance Comparison (PD=0.6)			
items	SS-IPDA	MSDF-IPDA	MS-IPDA
(a)	248	283	297
(b)	27	13	3
nCTT(Total)	275	296	300
nCTT Rate	91.67	98.67	100.00
nCFTScans	97	100	99
time(sec/run)	2.95	5.84	7.62

The MSDF-IPDA algorithm delivers significantly better

false track discrimination performance compared to the SS-IPDA algorithm. In the distributed system in cluttered environments, the MSDF-IPDA algorithm has track confirmation rate close to the centralized fusion scheme even in the case of low target detection probability. Using additional sensors is likely to further improve MSDF-IPDA performance.

VI. CONCLUSIONS

This paper presents the MS-IPDA algorithm for centralized fusion and the MSDF-IPDA algorithm for distributed fusion for multi-sensor single tracking in cluttered environments. The key issue is to develop algorithms for target existence probability calculation for fusion tracks for track maintenance. We demonstrate that the proposed approaches are useful in low target detection probability environments where they reveal fast and high confirmation rate superior than single sensor approaches. We also show that MSDF-IPDA is a viable solution for multi sensor fusion as it requires no excessive increase in computational cost compared to single sensor approaches and much less than MS-IPDA.

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