Track-to-track Fusion using Multiple Detection Linear Multitarget Integrated Probabilistic Data Association

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Abstract: The multi-sensor multiple detection target tracking problem is considered in this paper. The probability of target existence is used as the track quality measure and plays an important part in the fusion paradigm. The multiple detection linear multi-target integrated probabilistic data association (MD-LM-IPDA) is utilized and extended to the multi-sensor structure. Both centralized fusion MD-LM-IPDA and distributed track-to-track fusion MD-LM-IPDA are proposed. The centralized fusion method utilizes the information from all local sensors' measurements to get the best tracking performance but suffers from the high communication load. The distributed fusion method can control the communication load by adjusting the threshold for transmitting local tracks to the fusion center. One can make a choice between these two structures based on the tracking performance requirement and the computation resources.

1 INTRODUCTION

The multiple detection problem gained a substantial amount of attention in recent years due to that many kinds of high resolution sensors and radars are routinely used in many surveillance and tracking scenarios (Vivone et al., 1999; Baum and Hanebeck, 2014; Chen et al., 2014). In these multiple detection target tracking applications, the point target assumption, which allows each target generate at most one detection at each scan, cannot remain valid (Bar-Shalom et al., 2011). Instead, there can be more than one measurements come from the same object, the data association process need to enumerate the one-to-many track-to-measurements assignments and evaluate the corresponding posteriori data association probabilities. Both random matrix (Lan and Li, 2016) and measurement partition method (Mahler, 2009) are introduced to cover this multiple detection problem.

In target tracking applications, the real targets existence information is not known prior. The tracks can be initialized by both target measurements and clutter measurements which leads to the existence of both true tracks (tracking targets) and false tracks (tracking clutter) in the surveillance area (Musicki et al., 1994). The true track and false track states can be interchanged during tracking period based on the information extracted from the measurements. The probability of target existence is introduced as a judging standard of the existence of a target in order to solve the false track discrimination (FTD) problem, which involves true tracks confirmation and false track termination (Musicki and Evans, 2004; Musicki and Scala, 2008).

The multiple detection linear multitarget integrated probabilistic data association (MD-LM-IPDA), which embedded the measurement partition method into the LM-IPDA algorithm (Musicki and Scala, 2008), is an efficient method designed for multitarget multiple detection applications. In traditional MD structures (Habtemariam et al., 2013; Habtemariam et al., 2011), the selected measurements are partitioned into measurement cells, where each cell contains one or some of the selected measurements, and then these measurement cells are utilized in the joint track-to-measurement cell assignments. The MD-LM-IPDA bypass the joint track-to-measurement cell assignments process by treating the possible measurement cells of targets followed by other tracks as additional clutter measurements to modulate the clutter spatial density. This mechanism makes MD-LM-IPDA work efficiently in the closely spaced multitarget tracking applications but lose part of the optimality.

In the centralized fusion structure, the local sensors transmit measurements to the fusion center for global tracks update. This approach is optimal but usually not feasible due to the high communication

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load or for the reason that the local sensors only output the track information. The distributed track-to-track fusion approach focus on fusing the local sensor tracks with the global tracks at the fusion center. The performance of this approach is usually worse compared to centralized fusion method. However, the distributed track-to-track fusion approach requires only a fraction of the computation time needed for the centralized fusion since the number of local tracks transmitted to the fusion center is much less compared to the number of local sensor measurements (Musicki et al., 2015; Lee et al., 2014).

In this paper, both track-to-track fusion and centralized fusion are considered under the multiple detection situation. The MD-LM-IPDA is implemented in these two fusion structures. The probability of target existence is used as the track quality measure for local tracks and global tracks and only the confirmed local sensor tracks are sent to the fusion center for track-to-track fusion. In both these two fusion structures, the fusion center generates global tracks and uses local sensor output, tracks for track-to-track fusion and measurements for centralized fusion, to update global track states and probabilities of target existence.

In the track-to-track fusion structure, local sensors use the original measurements to update the local track states and the confirmed tracks (both true tracks or false tracks) are transmitted to the fusion center. Then, these confirmed tracks come form the local sensors assume the role of measurements to update the global track states at the fusion center. The probability of target existence of the local tracks are used in calculating the fusion probabilities. The fusion process improves both FTD and tracking accuracy compared to local sensor performance.

In the centralized fusion structure, all local sensors send the measurements to the fusion center and the global tracks are updated using these measurements. Usually the measurements used by the global tracks in centralized fusion is different from that of the distributed fusion. This different is due to that in the distributed fusion structure, each local sensor processes the tracking algorithm to generate tracks and confirmed local tracks are considered as measurements at the fusion center. Usually the centralized fusion obtains better performances than distributed fusion but plagued by the high communication burden.

Section 2 depicts the target and measurement models. Section 3 demonstrates the centralized fusion structure. The distributed fusion process is given in Section 4. In Section 5, the performances of the two fusion structures are compared followed by the conclusion in Section 6.

2 PROBLEM STATEMENT

The dynamic state for target τ propagates according to a constant velocity model, given by

$$x_{k+1}^{\tau} = F x_k^{\tau} + v_k \tag{1}$$

where x_k^{τ} stands for the target state at scan k, F is the state propagation matrix. v_k is the zero-mean Gaussian process noise with covariance Q.

The target measurement detected by sensor "s" is generated by

$$z_k^s = H^s x_k^{\tau} + w_k^s \tag{2}$$

where H_s is the measurement matrix and w_k^s is the zero-mean Gaussian measurement noise with covariance R^s. The process noise and measurement noise are assumed independent. Since the multiple detection problem is considered, each target can generate more than one measurements.

The clutter measurement follows the Poisson/uniform distribution which means that the number of clutter measurements at each scan follows Poisson distribution and the spatial distribution of a clutter measurement follows the uniform distribution in the surveillance area.

Let Z_k^s stand for the measurements obtained by sensor "s" and $z_{k,j}^s$ is the j-th measurement of Z_k^s. The measurements gathered by sensor "s" from initial to scan k is denoted by

$$Z^{k,s} = \{Z_1^s, Z_2^s, \ldots, Z_k^s\} \tag{3}$$

so that all the measurement obtained by all the sensors from initial to current scan k is given as

$$Z^k = \left\{Z^{k,1}, Z^{k,2}, \ldots, Z^{k,L}\right\} \tag{4}$$

where L is the number of sensors.

The probability of target existence event χ_k and not exist event $\overline{\chi}_k^{\tau}$ satisfies

$$P\left(\chi_k^{\tau}|Z^k\right) + P\left(\overline{\chi}_k^{\tau}|Z^k\right) = 1 \tag{5}$$

For reasons of clarity, here we define that

$$\hat{\psi}_k^{\tau} = P\left(\chi_k^{\tau}|Z^{k,s}\right); \overline{\psi}_k^{\tau} = P\left(\chi_k^{\tau}|Z^{k-1,s}\right) \tag{6}$$

and the prediction relation between these two parameters is given by

$$\overline{\psi}_k^{\tau} = p_{11}\hat{\psi}_{k-1}^{\tau} \tag{7}$$

where p_{11} is the propagation probability that a target exists at scan $k-1$ and keeps existence at scan k.

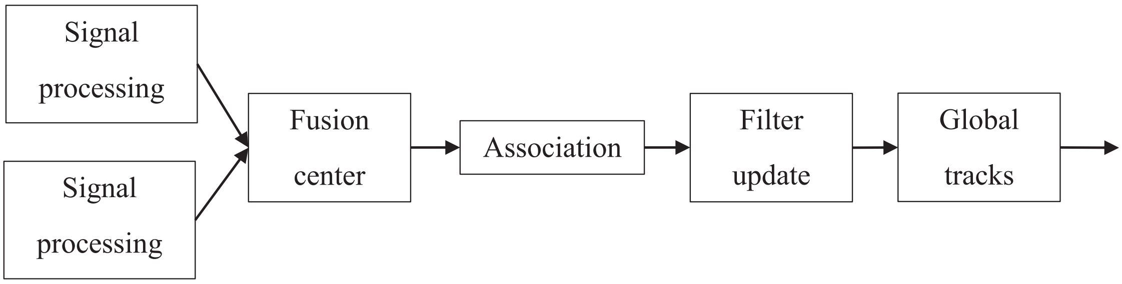

Figure 1: The structure of centralized fusion.

m_k^s	The number of measurements selected by sensor “s” at scan k
$\phi_{\tau,\max}$	The predetermined maximum number of target τ detections
$\varphi_{\tau,\max}$	The maximum number of target originated measurements in the m_k selected measurements, $\varphi_{\tau,\max} = \min(\phi_{\tau,\max}, m_k)$
$z^s_{\varphi_\tau,n_{\varphi_t}}(k)$	One measurement cell of track τ at time k
φ_τ	The number of measurements originated from target τ such that $1 \le \varphi_\tau \le \varphi_{\tau,\max}$
n_{φ_τ}	An index that indicates if the measurement cell $z_{\varphi_\tau,n_{\varphi_t}}(k)$ is one of the possible c_{φ_τ} combinations, where there are φ_τ measurements originating from target τ; $n_{\varphi_\tau} \in \{1,2,\ldots,c_{\varphi_\tau}\}$ and $c_{\varphi_\tau} = \frac{m_k!}{\varphi_\tau!(m_k-\varphi_\tau)!}$
$\chi^\tau_{k,0}$	The event that none of the selected measurements originated from target τ
$\chi^\tau_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}$	The event that measurement cell $z^s_{\varphi_\tau,n_{\varphi_\tau}}$ originated from target τ

3 CENTRALIZED FUSION STRUCTURE

In the multiple detection centralized fusion structure, each local sensor gathers measurements and sends these measurements to the fusion center. Some notations for algorithms derivation are given above and the structure of centralized fusion is shown in Figure 1.

Here, we use a simple example to show the measurement cells generated by the measurement partition method. Assuming that at scan k track τ selects two measurements $\left\{z^s_{k,1}, z^s_{k,4}\right\}$ out of the total $\left\{z^s_{k,1}, z^s_{k,2}, z^s_{k,3}, z^s_{k,4}\right\}$ and the corresponding partition events are:

- Only one of these two selected measurements is target detection ($\varphi_\tau = 1$), the number of possible combinations $c_{\varphi_\tau} = C_1^2 = 2$ and the n_{φ_τ} varies from 1 to 2. The measurement cells are:

$$z^s_{1,1}(k) = z^s_{k,1}$$
$$z^s_{1,2}(k) = z^s_{k,4}$$

- Both these two selected measurements are target detections ($\varphi_\tau = 2$), the number of possible combinations $c_{\varphi_\tau} = C_2^2 = 1$ and the n_{φ_τ} is 1. The measurement cell is:

$$z^s_{2,1}(k) = \left\{z^s_{k,1}, z^s_{k,4}\right\}$$

At the fusion center, the MD-LM-IPDA algorithm is used to update the global tracks using the local sensors measurements sequentially. For the brevity of notations, the time index k of the measurement cells are omitted and a brief description of this algorithm is given as follows:

$P^\tau_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}$ is defined as the a priori probability that target τ exists and measurement cell $z^s_{\varphi_\tau,n_{\varphi_\tau}}$ is generated by target τ. This probability is given by

$$\begin{aligned} P^\tau_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}} &\triangleq P\left(\chi^\tau_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}, \chi^\tau_k | Z^{k-1}\right) \\ &\approx \left(\frac{p^\tau_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}}{\rho^\tau_{z^s_{\varphi_\tau,n_{\varphi_\tau}}}} \Bigg/ \sum_{\varphi_\tau=1}^{\varphi_{\tau,\max}} \sum_{n_{\varphi_\tau}=1}^{c_{\varphi_\tau}} \frac{p^\tau_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}}{\rho^\tau_{z^s_{\varphi_\tau,n_{\varphi_\tau}}}} \right) \\ &\quad \cdot P^\tau_{D\varphi_\tau} (P^\tau_G)^{\varphi_\tau} \bar{\psi}^\tau_k \end{aligned} \tag{8}$$

where $p^\tau_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}$ is the measurement cell likelihood calculated by the same method as given in [10]. $P^\tau_{D\varphi_\tau}$ is the probability that detected a target φ_τ times. P^τ_G is the gating probability (Challa et al., 2011).

In (8), $\rho^\tau_{z^s_{\varphi_\tau,n_{\varphi_\tau}}}$ is calculated by

$$\rho^\tau_{z^s_{\varphi_\tau,n_{\varphi_\tau}}} = \prod_{z_j \in z^s_{\varphi_\tau,n_{\varphi_\tau}}} \left[\rho_{k,j} + \sum_{\substack{\sigma=1 \\ \sigma\neq\tau}}^{T} P^\sigma_{D1} (P^\sigma_G)^1 \bar{\psi}^\sigma_k \, p^\sigma_{k,j}\right] \tag{9}$$

where $p^\sigma_{k,j}$ is the measurement likelihood function of $z^s_{k,j}$ for track σ and $\rho_{k,j}$ stands for the clutter measurement density at point $z^s_{k,j}$.

Here, define $\tilde{\rho}^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}$ as the modulated clutter measurement density, satisfies

$$\tilde{\rho}^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}} \triangleq \rho_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}} + \sum_{\substack{\sigma=1\\ \sigma\neq\tau}}^{T} p^{\sigma}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}} \frac{P^{\sigma}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}}{1-P^{\sigma}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}} \tag{10}$$

where $\rho_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}} = \prod_{z^s_{k,j}\in z^s_{\varphi_\tau,n_{\varphi_\tau}}} \rho_{k,j}$.

The measurement likelihood ratio Λ^{τ}_k is defined by

$$\begin{aligned}\Lambda^{\tau}_k \triangleq & \frac{p\left(z_k|\chi^{\tau}_k, Z^{k-1}\right)}{p\left(z_k|\bar{\chi}^{\tau}_k, Z^{k-1}\right)}\\ \approx & 1-P^{\tau}_{Dec}\\ & + \sum_{\varphi_\tau=1}^{\varphi_{\tau,\max}} \sum_{n_{\varphi_\tau}=1}^{c_{\varphi_\tau}} \frac{p^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}}{\tilde{\rho}^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}} \varphi_\tau! P_{D\varphi_\tau}(P_G)^{\varphi_\tau}\end{aligned} \tag{11}$$

The a posteriori probability that target τ exists and there is no measurement generated by target τ is

$$P\left(\chi^{\tau}_{k,0}, \chi^{\tau}_k|Z^{k,s}\right) = \frac{\left(1-P^{\tau}_{Dec}\right)\bar{\psi}^{\tau}_k}{1-P^{\tau}_{Dec}\bar{\psi}^{\tau}_k} P\left(\chi^{\tau}_{k,0}|Z^{k,s}\right) \tag{12}$$

The a posteriori probability that target τ exists and measurement cell $z^s_{\varphi_\tau,n_{\varphi_\tau}}$ is the set of target τ detections satisfies

$$\begin{aligned}& P\left(\chi^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}, \chi^{\tau}_k|Z^{k,s}\right)\\ \approx & \frac{\bar{\psi}^{\tau}_k P^{\tau}_{D\varphi_\tau}\left(P^{\tau}_G\right)^{\varphi_\tau}}{1-\bar{\psi}^{\tau}_k\left(1-\Lambda^{\tau}_k\right)} \frac{p^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}}{\tilde{\rho}^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}} \varphi_\tau!\end{aligned} \tag{13}$$

The probability of target existence of track τ is updated by

$$\begin{aligned}P\left(\chi^{\tau}_k|Z^{k,s}\right) = & P\left(\chi^{\tau}_{k,0}, \chi^{\tau}_k|Z^{k,s}\right)\\ & + \sum_{\varphi_\tau=1}^{\varphi_{\tau,\max}} \sum_{n_{\varphi_\tau}=1}^{c_{\varphi_\tau}} P\left(\chi^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}, \chi^{\tau}_k|Z^{k,s}\right)\\ \approx & \frac{\Lambda^{\tau}_k\bar{\psi}^{\tau}_k}{1-P\bar{\psi}^{\tau}_k\left(1-\Lambda^{\tau}_k\right)}\end{aligned} \tag{14}$$

The data association probabilities are given by

$$\beta^{\tau}_{k,0} = \frac{P\left(\chi^{\tau}_{k,0}, \chi^{\tau}_k|Z^{k,s}\right)}{P\left(\chi^{\tau}_k|Z^{k,s}\right)} \approx \frac{1-P^{\tau}_{Dec}}{\Lambda^{\tau}_k} \tag{15}$$

and

$$\begin{aligned}\beta^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}} = & \frac{P\left(\chi^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}, \chi^{\tau}_k|Z^{k,s}\right)}{P\left(\chi^{\tau}_k|Z^{k,s}\right)}\\ \approx & \frac{P^{\tau}_{D\varphi_t}\left(P^{\tau}_G\right)^{\varphi_t}}{\Lambda^{\tau}_k} \frac{p^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}}{\tilde{\rho}^{\tau}_{k,z^s_{\varphi_\tau,n_{\varphi_\tau}}}} (\varphi_\tau!)\end{aligned} \tag{16}$$

Each measurement cell updates the track state using a modified Kalman filter [10] and together with the predicted state are used to generate the final track state by a Gaussian Mixture.

4 DISTRIBUTED TRACK-TO-TRACK FUSION STRUCTURE

The LM-IPDA algorithm is a suboptimal method for multitarget tracking/fusion problem in which the computational load is linear with the number of tracks. The confirmed local sensor tracks are used to update the global track states at the fusion center sequentially. Here we consider the situation that updating track τ using tracks $\{\zeta\}$ comes from sensor "s". In the track-to-track fusion structure, the tracks in $\{\zeta\}$ that follow other potential targets are treated as 'clutter' tracks with respect to τ. Then these 'clutter' tracks are used to modulate the clutter track density and by doing so the single target tracking approach is enabled to cover the multitarget tracking problem.

In the fusion center, the local tracks are treated as measurements and the a priori probability that measurement ζ comes from target τ is

$$P^{\tau}_{\zeta} = P_T\bar{\psi}^{\tau}_k \frac{\bar{\psi}^{\zeta}_k p^{\tau}_{\zeta}/\rho_\zeta}{\sum_{l\in\{\zeta\}}\bar{\psi}^{l}_k p^{\tau}_{l}/\rho_l} \tag{17}$$

where P_T is the track detection probability and the measurement likelihood p^{τ}_{ζ} is given by

$$p^{\tau}_{\zeta} = N\left(\hat{x}^{\zeta}_k; \hat{x}^{\tau}, S^{\tau}_{\zeta}\right) \tag{18}$$

and the parameters used in (18) will be given latter.

The ρ_ζ used in (17) is the clutter track density and a simple way to calculate this value is

$$\rho_\zeta = \frac{b}{V} \tag{19}$$

where b is the number of confirmed tracks transmitted to the fusion center by sensor "s" and V is the volume of the surveillance area.

The modulated clutter track density is defined as

$$\tilde{\rho}^{\tau}_{\zeta} \triangleq \rho_\zeta + \sum_{\sigma\neq\tau} \frac{P^{\sigma}_{\zeta}}{1-P^{\sigma}_{\zeta}} \bar{\psi}^{\zeta}_k p^{\sigma}_{\zeta} \tag{20}$$

where in this modulated clutter density, the possibility that track ζ is tracking another target is taken into consideration. This clutter track density expression is the core of the LM track-to-track fusion approach.

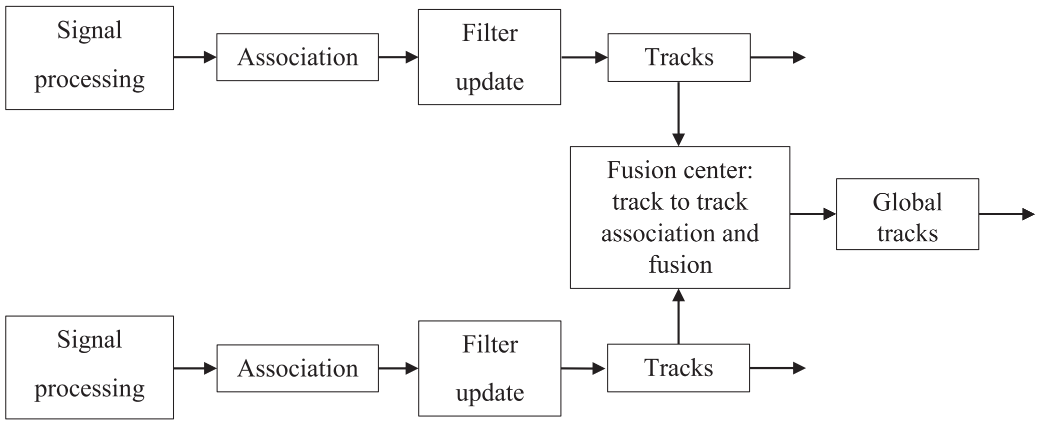

Figure 2: The structure of distributed fusion.

Then, the measurement likelihood ratio is expressed by

$$\Lambda^{\tau} = 1 - P_T + P_T \sum_{\zeta} \frac{\bar{\psi}_k^{\zeta} p_{\zeta}^{\tau}}{\tilde{\rho}_{\zeta}^{\tau}} \tag{21}$$

The a posteriori probability of target existence of track τ is updated by

$$\hat{\psi}_k^{\tau} = \frac{\Lambda^{\tau} \bar{\psi}_k^{\tau}}{1 - (1 - \Lambda^{\tau}) \bar{\psi}_k^{\tau}} \tag{22}$$

where $\bar{\psi}^{\tau}$ is the predicted target existence probability given in (7).

The track fusion probabilities, where the modulated clutter track density is used, can be obtained by

$$\beta_{\zeta}^{\tau} = \frac{1}{\Lambda^{\tau}} \begin{cases} 1 - P_T & \zeta = 0 \\ P_T \bar{\psi}_k^{\zeta} p_{\zeta}^{\tau} \big/ \rho_{\zeta} & \zeta > 0 \end{cases} \tag{23}$$

In the track-to-track fusion structure, even through the measurement noises of different sensors can be assumed independent there is still estimation errors correlate between two track if these two tracks are tracking the same targets (Bar-Shalom et al., 2011; Bar-Shalom, 1981; Bar-Shalom and Campo, 1986; Chen et al., 2003). So that the correlated Kalman filter (CKF) is employed for track state update.

The innovation covariance is generated by

$$S_{\zeta}^{\tau} = P_k^{\zeta} + P^{\tau} - P_{\zeta}^{\tau} - \left(P_{\zeta}^{\tau}\right)^T \tag{24}$$

where the cross covariance P_{ζ}^{τ} considers the correlated trajectory estimation errors between target ζ and τ, calculated by

$$P_{\zeta}^{\tau} = E\left[\left(\hat{x}_k^{\zeta} - x_k\right)\left(\hat{x}^{\tau} - x_k\right)\right] \tag{25}$$

The Kalman gain is calculated by

$$K_{\zeta}^{\tau} = \left(P^{\tau} - P_{\zeta}^{\tau}\right)\left(S_{\zeta}^{\tau}\right)^{-1} \tag{26}$$

The track state and corresponding covariance are updated by

$$\hat{x}_{\zeta}^{\tau} = \hat{x}^{\tau} + K_{\zeta}^{\tau}\left(\hat{x}_k^{\zeta} - \hat{x}^{\tau}\right) \tag{27}$$

and

$$\begin{aligned} P_{\zeta}^{\tau} = {} & \left(I - K_{\zeta}^{\tau}\right) P^{\tau} \left(I - K_{\zeta}^{\tau}\right)^T + K_{\zeta}^{\tau} P_k^{\zeta} \left(K_{\zeta}^{\tau}\right)^T \\ & + \left(I - K_{\zeta}^{\tau}\right) P_{\zeta}^{\tau} \left(K_{\zeta}^{\tau}\right)^T + K_{\zeta}^{\tau} \left(P_{\zeta}^{\tau}\right)^T \left(I - K_{\zeta}^{\tau}\right)^T \end{aligned} \tag{28}$$

In the distributed track-to-track fusion structure, the global tracks in the fusion center are updated by the local sensor tracks sequentially. In all above equations, the state and state covariance for target τ are not specified by a time index k. When track τ is fused with the first sensor's local tracks, the predicted information $\hat{x}_{k|k-1}^{\tau}$ and $P_{k|k-1}^{\tau}$ are used as $\hat{x}^{\tau}$ and P^{τ}. Then, in order to fuse with the second sensor's local tracks, the updated state $\hat{x}_{\zeta}^{\tau}$ and state covariance P_{ζ}^{τ} are used as $\hat{x}^{\tau}$ and P^{τ}. In the probability of target existence update recursion, the predicted existence probability $\bar{\psi}_k^{\tau}$ is updated using the first sensor's confirmed tracks information. When this parameter is updated by the second sensor, the updated existence probability $\hat{\psi}_k^{\tau}$ is used as the predicted information for the second sensor.

5 SIMULATION STUDIES

Two simulations are considered in this part, one is used for comparing different fusion structures and the other is used for comparing multiple detection structure with single detection structure.

Table 1: Simulation parameters.

	Centralized	T2TF	T2TF-2	Sensor1	Sensor2	Sensor3
Initial PTE	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Confirmed threshold (local)	–	0.001	0.1	0.999	0.999	0.999
Confirmed threshold (fusion center)	0.99	0.95	0.97	–	–	–
P_d	$[0.4, 0.3]$	–	–	$[0.4, 0.3]$	$[0.4, 0.3]$	$[0.4, 0.3]$
P_T	–	0.7	0.7	–	–	–
Number of confirmed false tracks	1	1	1	1	2	2
Simulation time (per each run)	13.27s	0.31s	0.26s	0.27s	0.28s	0.28s

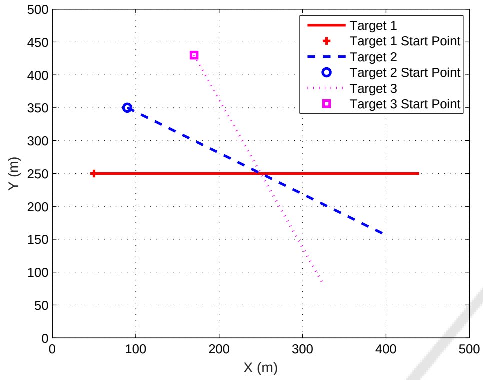

Figure 3: Simulation scenario.

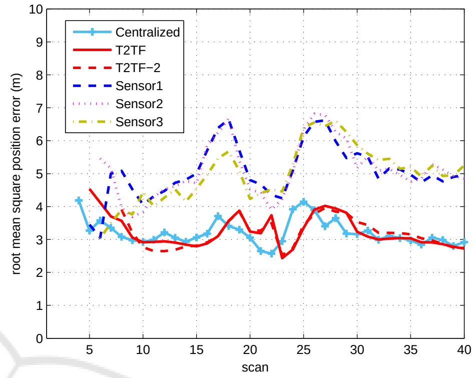

Figure 5: Root mean square position error of target 2.

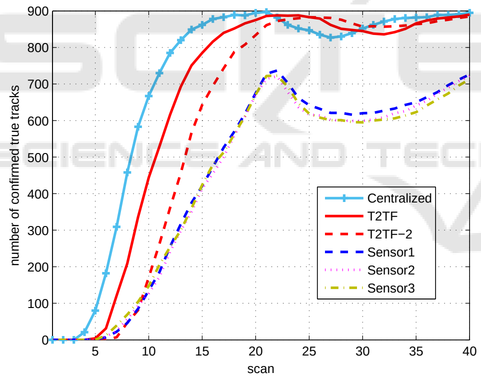

Figure 4: Confirmed true tracks for all the targets.

5.1 Simulation One

In this simulation scenario, three targets move in a $500m \times 500m$ Cartesian coordinates with the constant velocities. All of them reach the same location $[250m, 250m]$ at scan 20. Totally 300 Monte Carlo simulation runs where each run contains 40 scans with the scan interval equal to 1s. Three sensors are used to detect targets, all these sensors are located at the origin of the coordinates and each detects targets independent from the others. In this simulation, the multiple detection problem is considered where the detection probability of the local sensors and centralized fusion structure is set as $[0.4, 0.3]$ which denotes that each sensor obtains one detection from a target with probability 0.4 and two detections from a target with probability 0.3. In the distributed fusion structure, the track detection probability P_T at the fusion center is set as 0.7. The average number of clutter measurements occurs at each scan for each sensor is 25.

The target state propagation matrix and the process noise covariance are given as

$$F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{29}$$

and

$$Q = 0.75m^2s^{-3} \begin{bmatrix} T^3/3 & 0 & T^2/2 & 0 \\ 0 & T^3/3 & 0 & T^2/2 \\ T^2/2 & 0 & T & 0 \\ 0 & T^2/2 & 0 & T \end{bmatrix} \tag{30}$$

The process noise covariance is given by

$$R = \begin{bmatrix} 25 & 0 \\ 0 & 25 \end{bmatrix} \tag{31}$$

The initial states of these three targets are

$$\begin{array}{ll} \text{target 1}: & \begin{bmatrix} 50m & 250m & 10m/s & 0m/s \end{bmatrix} \\ \text{target 2}: & \begin{bmatrix} 90m & 350m & 8m/s & -5m/s \end{bmatrix} \\ \text{target 3}: & \begin{bmatrix} 170m & 430m & 4m/s & -9m/s \end{bmatrix} \end{array} \tag{32}$$

Each local sensor utilizes the MD-LM-IPDA algorithm for tracking targets. The probability of target existence is used to solve the FTD problem. Once the probability of a track exceeds the confirmed threshold, it remains confirmed state. All the local sensors' performances are shown and compared with distributed and centralized fusion structures.

In the track-to-track fusion (T2TF) structure, after each sensor utilizes the MD-LM-IPDA algorithm, the confirmed local tracks of each sensor are transmitted to the fusion center and then the global tracks are fused with local confirmed tracks sequentially using the method proposed in Section IV. The track confirmed threshold used for selecting local tracks to transmit to the fusion center can be adjusted to control the number of tracks transmitted. The influence of this parameter can be seen from Figure 4 and Figure 5 where two different performances obtained by using different values for the local track confirmed threshold are demonstrated (T2TF and T2TF-2).

The centralized fusion implements tracking process using each sensor's measurements sequentially. This optimal fusion framework immediately extracts targets information from local sensor measurements, which obtains the best performance compared to other fusion structures but not always feasible due to both communication load and computational burden.

The simulation parameters for different algorithms are shown in Table I. The initial probabilities of target existence (PTE) for different algorithms are set the same and the confirmed thresholds are adjusted in order to obtain almost same number of confirmed false tracks. The method for adjusting whether a track is a confirmed true track or a confirmed false track is the same as given in (Musicki et al., 2013).

The number of confirmed true tracks of different algorithms are shown in Figure 4. The tracking performance after using fusion paradigm is much better compared to that of the single sensor. The fusion process enhances the target existence information, the centralized fusion method obtains the best performance as expected. The performance of track-to-track fusion process is worse than centralized method but much more efficient in the sense of computational expense. And the performance of track-to-track fusion using a lower local track confirmed threshold is better compared to the one uses higher value because more information is transmitted to the fusion center.

In Figure 5, the root mean square position errors are shown. The position estimates after fusion are more accurate compared to single sensor performances. Since both centralized and distributed fusion take advantage of the information from all the sensors, they obtain similar performances.

Here the average number of measurements obtained by each sensor at each scan over 300 runs and the average number of confirmed tracks (treated as measurements at the fusion center) transmitted to the fusion center of each sensor at each scan over 300 runs are shown in Figure 6. This figure indicates that in the distributed fusion structure, local sensor transmits much less information to the fusion center which makes this structure more efficient compared to centralized fusion especially in high clutter environment. When adjusting the confirmed threshold, the number of tracks transmitter to the fusion center changed a little bit, this is due to the fact that the tracks excluding confirmed true tracks cannot survive for a long period (they are merged or terminated).

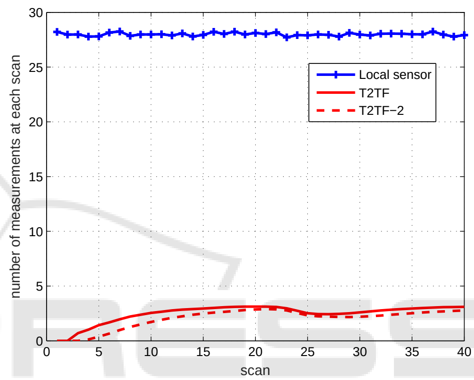

Figure 6: Number of measurements at each scan.

5.2 Simulation Two

The simulation scenario demonstrated in Figure 3 is applied. Only distributed fusion structure is considered to compare MD-LM-IPDA and LM-IPDA in order to show the difference between multiple detection structure and single detection structure. The simulation parameters used by these two algorithms are shown in Table 2 and the other parameters about targets and environment background are the same as those given in subsection 5.1.

Figure 7 demonstrates the number of confirmed true tracks for all these three targets. It is obvious that MD-LM-IPDA has a bitter performance compared to LM-IPDA in the sense of true track confirmation. The root mean square position errors for each of these three targets are similar so that only the performance for target 2 is shown in Figure 8. From this figure, we can see that the target state estimation error of MD-LM-IPDA is lower than that of LM-IPDA.

Table 2: Simulation parameters.

	LM-IPDA	MD-LM-IPDA
Initial PTE	0.0001	0.0001
Confirmed threshold (local)	0.1	0.1
Confirmed threshold (fusion center)	0.97	0.97
P_d	0.7	$[0.4, 0.3]$
P_T	0.7	0.7
Number of confirmed false tracks	1	1
Simulation time (per each run)	0.24s	0.26s

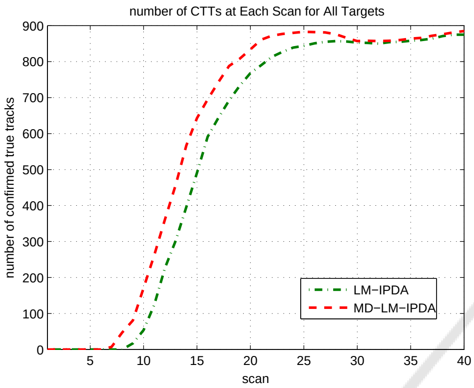

Figure 7: Confirmed true tracks for all the targets.

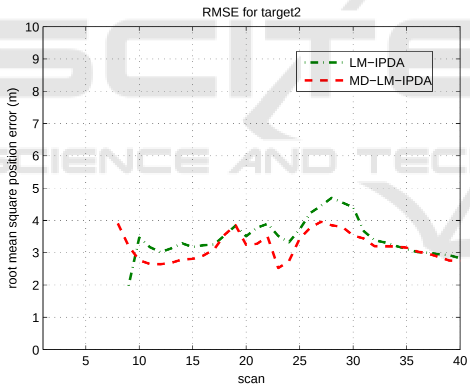

Figure 8: Root mean square position error of target 2.

6 CONCLUSIONS

In this paper, we propose both centralized and distributed fusion structures based on a suboptimal multiple detection multitarget tracking algorithm called MD-LM-IPDA. These two structures utilize the probability of target existence to cover the true track confirmation and false track discrimination problem.

In the distributed fusion paradigm, local sensor uses the target existence information to confirm tracks. Only confirmed tracks are transmitted to the fusion center and used as measurements to update global tracks. By adjusting the local track confirmed threshold, the amount of information (track states and target existence probabilities) transmitted to the fusion center can be controlled.

Since centralized fusion utilizes the information from all the measurements, it obtains the best performance with a high communication burden between local sensors and fusion center. In distributed fusion structure, local sensors process tracking algorithm to generate tracks and send high quality tracks (with high probability of target existence) to the fusion center which makes this structure more feasible in many practical applications.

When distributed fusion structure is considered, MD-LM-IPDA outperforms LM-IPDA in the sense of true track confirmation and state estimation accuracy. This performance superiority of MD-LM-IPDA is due to that multiple detection structure helps to extract target state information contained in measurements by considering more possible target oriented measurement combinations.

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REFERENCES

Bar-Shalom, Y. (1981). On the track-to-track correlation problem. *IEEE Trans. Automat. Contr.*, 26(2):571–572.

Bar-Shalom, Y. and Campo, L. (1986). The effect of the common process noise on the two-sensor fused-track covariance. *IEEE Trans. Aerosp. Electron. Syst.*, 22(6):803–805.

Bar-Shalom, Y., Willett, P., and Tian, X. (2011). *Tracking and Data Fusion*. YBS, Storrs, 1st edition.

Baum, M. and Hanebeck, U. D. (2014). Extended object tracking with random hypersurface models. *IEEE Trans. Aerosp. Electron. Syst.*, 50(1):149–159.

Challa, S., Evans, R., Morelande, M., and Musicki, D. (2011). *Fundamentals of Object Tracking*. Cambridge University, United Kingdom., 1st edition.

Chen, H., Kirubarajan, T., and Bar-Shalom, Y. (2003). Performance limits of track-to-track fusion versus centralized estimation: Theory and applications. *IEEE Trans. Aerosp. Electron. Syst.*, 39(2):386–400.

Chen, J. F., Ma, H., Liang, C. G., and Zhang, Y. F. (2014). OTHR multipath tracking using the bernoulli filter. *IEEE Trans. Aerosp. Electron. Syst.*, 50(3):1974–1990.

Habtemariam, B., Tharmarasa, R., Thayaparan, T., Grimmett, D., and Wakayama, C. (2011). Multiple detection probabilistic data association filter for multistatic target tracking. In *4th Int. Conf. Information Fusion*.

Habtemariam, B., Tharmarasa, R., Thayaparan, T., Mallick, M., and Kirubarajan, T. (2013). A multiple-detection joint probabilistic data association filter. *IEEE Trans. Aerosp. Electron. Syst.*, 7(3):461–471.

Lan, J. and Li, X. R. (2016). OTHR multipath tracking using the bernoulli filter. *IEEE Trans. Aerosp. Electron. Syst.*, 52(6):2973–2989.

Lee, E. H., Musicki, D., and Song, T. L. (2014). Multisensor distributed fusion based on integrated probabilistic data association. In *17th Int. Conf. Information Fusion*.

Mahler, R. (2009). PHD filters for nonstandard targets, I: Extended targets. In *12th Int. Conf. Information Fusion*.

Musicki, D. and Evans, R. (2004). Joint integrated probabilistic data association: JIPDA. *IEEE Trans. Aerosp. Electron. Syst.*, 40(3):1093–1099.

Musicki, D., Evans, R., and Stankovic, S. (1994). Integrated probabilistic data association (IPDA). *IEEE Trans. Automat. Contr.*, 39(6):1237–1241.

Musicki, D. and Scala, B. L. (2008). Multi-target tracking in clutter without measurement assignment. *IEEE Trans. Aerosp. Electron. Syst.*, 44(3):877–896.

Musicki, D., Song, T. L., and Kim, T. H. (2013). Smoothing multi-scan target tracking in clutter. *IEEE Trans. on Signal Process.*, 61(19):4740–4752.

Musicki, D., Song, T. L., Lee, H. H., Chen, X., and Kirubarajan, T. (2015). Track-to-track fusion with target existence. *IET Radar, Sonar Navig.*, 9(3):241–248.

Vivone, G., Braca, P., Granstrom, K., and Willett, P. (1999). Multistatic bayesian extended target tracking. *IEEE Trans. Aerosp. Electron. Syst.*, 25(6):2626–2643.