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An Adaptive Density-Based Fuzzy Clustering Track Association for Distributed Tracking System

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ABSTRACT The problem of duplicate track determination called "Track-to-Track association" occurs when a target is reported by different sensors, and it is regarded as one of the most important challenges in distributed multi-sensor tracking systems. The present study aimed to propose a density-based fuzzy clustering method for solving the track-to-track association problem in distributed multi-sensor tracking systems. Unlike the previously published solutions, the proposed method does not need any information about the number of targets, due to the use of the density-based clustering approach. Proposed method has low computational overhead and can be used in real-time tracking systems. In addition, the proposed method uses the maximum entropy approach to determine the membership degree of single target related tracks and combines them. This paper presents three scenarios including sensors with complete and incomplete overlapping by considering the bias and a different number of sensors and targets for evaluating the proposed method based on the Monte Carlo simulation. The results indicate the improvement of the efficiency in comparison with the FTF approach. The efficiency of proposed method's results is close to the results of Bayesian minimum mean square error criterion that gives best possible results.

INDEX TERMS Density clustering, distributed target tracking, multi sensor fusion, track association.

I. INTRODUCTION

During recent years, the combination of information obtained from multi-sensor systems has been considered as one of the attractive research areas regarding the variety of its applications. Targets tracking is one of the most important applications of multi-sensor systems that achieves more accurate and reliable results. Based on the sensor's architecture, multi-sensor based tracking systems can be categorized into 1) centralized and 2) distributed. In centralized architecture-based tracking systems, sensors send the received raw measurements to the fusion center (FC), which combines these measurements and estimate target's state [1]–[4].

Other type of multi-sensor tracking system is the distributed tracking system, which each sensor estimates target's state individually and sends them to the FC. Centralized tracking methods yields more accurate results in comparison with distributed tracking methods. However, centralised methods in comparison with distributed methods 1) require higher computing power in the FC, 2) need for high data transfer rate for sending measurements of sensors to the FC and 3) have high vulnerability in the case of failure in the FC [5], [6]. Given the expressed issues, the distributed tracking systems have higher acceptability and application than that of centralized tracking systems [7].

The distributed tracking systems benefits from modularity, practicality and scalability compared to the centralized tracking systems. In this architecture, after local tracking by each sensor, all tracks are sent to the FC for combination. Due to the lack of information of the sensor overlapping and the number of targets in FC, it is necessary to determine the number of targets and duplicate tracks for combining. The action of determining duplicate tracks is known as track-to-track association (TTTA) [8]–[12].

Different types of TTTA methodologies have been developed in recent years, which are usually computationally expensive and are unsuitable for real-time applications. Accordingly, TTTA techniques based on fuzzy clustering have been interested. However, due to the lack of information about number of targets, fuzzy clustering based TTTA algorithms have significant computational complexity. To overcome this problem, a novel density-based fuzzy clustering

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TTTA for tracking multiple targets in distributed multi-sensor tracking systems that do not need number of targets to be known in advance is proposed in this paper. Beyond that, the proposed technique has a negligible computational cost and can be used in real-time applications.

The rest of paper is organized as follows. Section II presents the related works. The problem formulation and assumptions are presented in Section III. The proposed fuzzy density-based spatial clustering track association (FDBSC-TA) is described in Section IV. Computer simulations' results are shown in Section V. Finally, the conclusions are presented in Section VI.

II. RELATED WORKS

During recent years, highly efficient track–to-track association methods are presented, which can be classified to 1) distance based algorithms, 2) probability-based algorithms and 3) other information-aided algorithms [13]. Singer and Kanyuck [14] developed the first TTTA technique in 1970 to estimate two tracks from two different systems based on using Gates. In [15], the TTTA technique using the covariance-based test statistic by assuming the independence of the error of various systems was proposed. A robust Dempster-Shafer fusion (RDSF) algorithm was proposed based on accumulated information [2]. This method uses a heuristic Dempster-Shafer to determine the relationship of local tracks and fused tracks. A novel track-association approach according to combined of the track disposition and the estimated track history is designed by Lee *et al.* [16]. Their approach was based on geometric arrangement of the track and the estimated track history, respectively. Liu *et al.* [17] have suggested a new track-to-track association algorithm based on well-known iterative closest point (ICP) and global nearest neighbour (GNN). The proposed method is employed for marine surveillance by GF-4 satellite in the specific area of the East China Sea. These studies haven't considered the biases of the sensors, which are existed in reality.

Presence of sensor biases lead to performance degradation of the traditional TTTA algorithms. Therefore, it is necessary to remove sensor biases before applying TTTA. Existence of biases in sensors lead to large deviations between estimated state and real state of a target. Also, bias estimation is highly conditioned on the results of TTTA. In consequence, TTTA and sensor bias estimation are highly coupled with each other [8], [18]. Therefore, effective methods were introduced to solve TTTA and sensor bias estimation [6]–[8], [19]–[21]. A joint approach for solving problem of track-to-track association and sensor bias estimation is suggested by Zhu and Wang [6]. In [20], an anti-bias track-to-track association technique is designed for aircraft platforms according to statistical characteristic of Gaussian random vectors. Tian *et al.* are stated a track-to-track association algorithm based on the reference topology (RET) feature [18], which avoids estimating the relative bias. However, most of these methodologies have considered just two sensors for tracking, whereas in real applications like wireless sensor networks there are more than two sensors.

Generally, determining the optimal response for TTTA and track fusion (TF) has high computational load. Accordingly, the use of suboptimal techniques are more preferred than complex optimal methods [1], [22], [23]. The suboptimal techniques are based on neural network [24], [25] and fuzzy clustering [13], [26], [27]. The neural network-based techniques have been less considered due to the high number of neurons and the training based on a large number of tracks collections, while fuzzy TTTA techniques have been developed in recent years. The fuzzy clustering-based TTTA was developed to determine the membership degree of observations in a multi-sensor multi-target environment. The fuzzy TTTA was presented based on the Dempster–Shafer theory by Fan *et al.* [28]. Authors have evaluated the feature of sensors and use tracks to determine the combined belief functions. Aziz [1] applied the fuzzy C-means (FCM) to determine the membership degree of tracking targets with overlapping and information such as sensor resolutions to combine tracks. Also, he presented TTTA and fuzzy TF techniques in a distributed multi-sensor multi-target environment for scenarios with incomplete overlapping of sensors. In addition, due to the complexity of determining duplicate and non-duplicate tracks in applications with a large number of sensors and targets, it is necessary to use the cluster analysis-based methods. The number of ways used to cluster n tracks into c clusters is calculated as follows [1]:

$$S_n^{(c)} = \frac{1}{c!} \sum\nolimits_{k=0}^{c} \binom{c}{k} k^n \tag{1}$$

This problem becomes more complex when FC does not know the number of clusters (targets). Generally, creating an optimal solution to the TTTA problem and tracks combination are usually costly and inappropriate for real-time systems. The lack of knowing the actual number of targets in multi-sensor multi-target tracking systems increases the complexity of the problem, which necessitates clustering and clusters analysis.

The density-based clustering approach is regarded as one of the most widely used clustering methods in data mining [29]–[33]. The lack of need to know the number of clusters, one scan, noise management and the ability to discover clusters with any desired shape are among the most important features of this clustering method. In [34], we developed a robust fuzzy density clustering joint probability data association filter (FD-JPDAF) to solve the data association problem in single sensor tracking systems. In single sensor tracking systems, the gating technique is usually used prior to data association to eliminate invalid measurements. Our proposed fuzzy density-based data association filter (FD-JPDAF) facilitates valid measurement selection and does not need gating technique.

In current study, an adaptive density-based fuzzy clustering is used for determining the duplicate tracks and doing fusion in FC, while FD-JPDAF are used as local tracks estimators in sensors. Proposed TTTA method of this paper gets tracks of targets from different sensors and then relates them. After that, it uses prior estimated state of each target as basis for determining fuzzy membership of reported tracks of sensors that are related to a single target. These fuzzy membership values will be used for weighted combinations of reported tracks of a single target to produce a fused target state that will be used by applications. The ability to perform TTTA and TF of the proposed algorithm in presence of sensor bias are presented by simulation results based on Monte Carlo simulation. Finally, the main contributions and significant features of the developed method can be summarized as follows:

- It is not limited to specific number of targets and sensors.
- It does not need to know the number of targets and sensors as priori.
- Computational cost of proposed method in worst case scenario is quadratic.
- It can integrate with other track fusion methods.
- The bias of the sensors is considered and the proposed approach has tried to reduce its effect.

III. PROBLEM FORMULATION & ASSUMPTIONS

A. FORMULATION

Table 1 lists the notations used in this article. Let assume a set of n sensors, which monitor T targets in the distributed sensor networks. In addition, the sensors are overlapped and their position is well-known.

TABLE 1. Main mathematical symbols.

$\hat{x}_{t,s}(k\|k)$	target state at the sensor s at time k
$\hat{x}_t(k\|k)$	target state at the fusion center of target t at time k
$\hat{p}^s_t(k\|k)$	target covariance matrix at the sensor s at time k
$\hat{p}_t(k\|k)$	target covariance matrix at the fusion center of target t at time k
$C_{t,k}$	center of cluster t at time k
U_t	local tracks set of target t
u^i_t	fuzzy membership degree of track i belonging to the target t
$\hat{\eta}^s_k$	bias vector of sensor s at time step k
T	the number of targets
n^t	the number of tracks belonging to the target t
n^s	the number of tracks report by sensor s
D_x	the set of local tracks states
D_p	the set of local tracks covariance matrix

The dynamics and measurement models of targets are defined as:

$$x(k) = f(x(k-1)) + w(k) \tag{2}$$
$$z(k) = h(x(k)) + \eta_k + v(k) \tag{3}$$

where $x(k) = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T$ is an n-dimensional state vector, and $z(k) = [r_k, \theta_k]^T$ is an m-dimensional measurement vector of the j^{th} target at time k. $f(.)$ is a known non-linear function, $h(.)$ is a known non-linear function and η_k is the bias vector. The process noise w_k and measurement noise $v(k)$ are assumed to be zero mean Gaussian noise vectors with known covariance Q_k andR_k, respectively.

$$Q_k = Cov(w(k)) \tag{4}$$
$$R_k = Cov(v(k)) \tag{5}$$

Each sensor independently estimates the state of the targets based on the measurements received from its surveillance environment and sends it to the FC. The local estimates are displayed as a tuple $\{\{\hat{x}_{t,s}(k|k), \hat{p}^s_t(k \mid k)\}|s = 1, \ldots, n, t = 1..T\}$, where $\hat{x}_{t,s}(k|k)$ and $\hat{p}^s_t(k \mid k)$ respectively are the state estimate and corresponding covariance matrix which are sent to the FC for combination.

B. ASSUMPTIONS

As mentioned above, one the most important property of proposed method is that, it is not limited to specific number of targets and do not require prior assumption about number of targets. However, we have considered the following assumptions.

Assumption 1: Sending and receiving of signals in both of sensors and fusion center are reliable and considered to be without delay, and local tracks are simultaneous.

Assumption 2: The multiple local sensors may detect multiple targets in cluttered environments.

Assumption 3: The process and measurement noises and environment clutter are assumed zero mean Gaussian noise and spatially Poisson distributed, respectively.

IV. FUZZY DENSITY BASED SPACIAL CLUSTERING TRACK ASSOCIATION

This section describes the proposed method for solving TTTA and TF problems for distributed tracking systems.

A. TRACK ASSOCIATION

As discussed in Section 1, it is not easy to determine duplicate and non-duplicate tracks in applications with high number of sensors and targets, and accordingly use of the clustering methods are required. In this section, we proposed a new method based on the density-based fuzzy clustering for solving the TTTA problem.

Generally, the purpose of the TTTA is to determine duplicate and non-duplicate tracks. The proposed method solves the TTTA problem in two stages of tracks clustering and determining the membership degree of duplicate tracks. The method requires only the *Eps* (maximum radius of the neighborhood) parameter for track clustering. Proposed method starts with a random selection of a track from the received tracks set (D_x) and considers it as the first member of the first cluster in the process of tracks clustering. Then, all *Eps_neighborhood* (tracks with the maximum

Eps distance) are recovered from the selected tracking and considered as cluster members. This process continues until the *Eps_neighborhood* of all cluster member tracks are recovered. The determined tracks are known as the members of the first cluster and in fact are duplicate tracks which are estimated by different sensors and are reported to FC. The above process continues for the remaining of the non-processed (non-clustered) tracks. At the end of the clustering process, the number of formed clusters will be equal to the number of targets in the surveillance environment, and the members of each cluster will be duplicate tracks of targets.

In the second part of the proposed TTTA method, the membership degree of duplicate tracks of a cluster is calculated separately for each cluster to solve the TF problem. Suppose that $U_t = \{\hat{x}_{t,i}(k|k), \hat{p}_i^t(k|k)|\textit{tracks of target } \boldsymbol{t} \textit{ are reprot by sensors}\}$ is the member tracks set of cluster t (duplicate tracks reported from the target t). Thus, the membership degree of each member track of this set is determined by the principle of maximum entropy as follows [35], [36]:

$$u_t^i = \frac{e^{-\alpha_{opt} d\left(\hat{x}_{t,i}(k|k), C_{t,k}\right)}}{\sum_{j=1}^{n^t} e^{-\alpha_{opt} d\left(\hat{x}_{t,j}(k|k), C_{t,k}\right)}}, \quad i = 1, .., n^t \tag{6}$$

where $C_{t,k}$ represents the center of the cluster t and is considered as follows for simplicity:

$$C_{t,k} = f\left(\hat{x}_t\left(k-1 \mid k-1\right)\right) \tag{7}$$

where $d\left(\hat{x}_{t,i}(k|k), C_{t,k}\right)$ indicates the Euclidean distance between the track $\hat{x}_{t,i}(k|k)$ and the center of the cluster t. n^t denotes the number of duplicate tracks from the target, which is equal to the number of sensors when the target is located in the surveillance area of all sensors. Finally, α_{opt} is the Lagrange coefficient known as the discriminating factor and its optimal value is calculated as follows [35], [37]:

$$\alpha_{opt} = -\frac{\ln \varepsilon}{d_{min}}, \quad \varepsilon = 0.000001 \tag{8}$$

Further, $\hat{x}_t\ (k-1 \mid k-1)$ estimates the calculated track of the track combination (TF) from the target t in the previous step (*k-1*). The above procedure is repeated for all clusters independently.

B. TRACK FUSION

Further, $\hat{x}_t\ (k-1 \mid k-1)$ estimates the calculated track of the track combination from the target t in the previous step (*k-1*). The above procedure is repeated for all clusters independently.

After solving the TTTA problem and determining the duplicate tracks, it is possible to combine them and estimate a unique set of tracks in FC. Given the determined importance degree (weight) of duplicate tracks, their weighted combination is proposed for FC.

$$\hat{x}_t\ (k \mid k) = \sum_{j=1}^{n^t} u_t^j.(\hat{x}_{j,t}\ (k \mid k)) \tag{9}$$

$$\hat{p}_t\ (k \mid k) = \sum_{j=1}^{n^t} \Big[\hat{p}_{j,t}\ (k \mid k) + \left(\hat{x}_{j,t}\ (k \mid k) - \hat{x}_t\ (k \mid k)\right) \times \left(\hat{x}_{j,t}\ (k \mid k) - \hat{x}_t\ (k \mid k)\right)^T\Big] \tag{10}$$

where $\hat{x}_t\ (k \mid k)$ is used in step $(k+1)$ to estimate the center of the cluster t. The above relationship must be repeated for all targets $(t = 1, \ldots, T)$. Algorithm 1 illustrates the proposed algorithm for the TTTA and TF problems.

C. COMPUTETION COMPLXITY

As shown in Algorithm 1, the proposed method consists of three main phases, 1) local tracks clustering, 2) determining the membership degree of duplicate tracks and 3) tracks combination. Assume tracking system contains n sensors and in worst case scenario sensors have complete overlap. This means that each sensor can sense all targets. Let assume that T targets are exist in environment, the D_x set in worst case includes $m = (n \times T)$ local tracks, which are reported to FC. The clustering phase has a time order proportional to $O(T \times m)$ for clustering m tracks. Each iteration of *while* loop in Algorithm 1 yields a cluster for each target. The number of repetitions of *while* loop is equal with number of targets and in each iteration of loop, determining the *Eps_neighborhood* of the cluster members has $O(m)$.

Determining the membership degree of tracks is accomplished within two nested *for* loops, which outer loop repeats *no_of_clusters* times and inner loop repeats n^t times that in the worst case n^t is equal with the number of sensors (n). This worst case occurs when all sensors sense all targets. Furthermore, in worst case, order of calculating the membership degrees of sensed tracks for each target is $O(n)$. As a result, the order of this step is $O\left((n \times T) \times n\right) = O(T \times n^2)$.

Finally, the combination of tracks is independently performed for each target (cluster) in the last loop. This is accomplished for T targets and in worst case, fusion of local tracks of n sensors is performed with the order of $O\left(T \times n\right)$. Therefore, the order of the proposed method is equal to $O(T \times n^2)$.

V. SIMULATIONS

In the present section three scenarios are suggested to evaluate the proposed method compared to FTF [1] and Bayesian minimum mean square error (MMSE) [38], [39]. In all scenarios, it is assumed that local tracking on the sensors are independently performed by FD-JPDAF [34] based on received measurements, and the estimated status of targets are sent to the FC for the combination. Additionally, the clutter model is assumed to be spatially Poisson distributed with known parameter $\lambda = 1$ (the number of false measurements per unit of volume (km^2)) [40].

For accurate evaluation, the root mean square error (RMSE) criterion was calculated based on 100-runs of Monte Carlo simulation.

$$RMSE = \sqrt{(\hat{x} - x_{true})^2 + (\hat{y} - y_{true})^2} \tag{11}$$

where $(\hat{x}, \hat{y})$ and(x_{true}, y_{true}) denote the estimated and true target positions, respectively.

As mentioned in section III, the proposed method has just one parameter (*Eps*) for tracks clustering. Having only one

Algorithm 1 Fuzzy Density-Based Spatial Clustering Track Association (FDBSC-TA)

Input: the local tracks state and covariance matrix $\hat{x}_t^s\,(k\mid k)\,,\hat{p}_t^s(k|k)\}$

Output: global tracks state and its corresponding covariance matrix $\{\hat{x}_t\,(k\mid k)\,,\hat{p}_t\,(k\mid k)\}$

1. $D_{unprocessed} = D_x$
2. $no\_of\_clusters = 0$
3. **While** $\left(D_{unprocessed} \neq \emptyset\right)$ **do**
4. Arbitrary select a $p \in D_{unprocessed}$
5. $D_{unprocessed} = D_{unprocessed} - p$
6. $no\_of\_clusters + +$
7. $\{p\} addtocluster_{no\_of\_clusters}$
8. $Eps\_neighborhood\_set =$ $DetermineallEps\_neighborhoodinD_x fromp$
9. **For** $eachqfromEps\_neighborhood\_set$ **do**
10. $D_{unprocessed} = D_{unprocessed} - q$
11. $qaddtocluster_{no\_of\_clusters}$
12. add all $Eps\_neighborhood$ q to $Eps\_neighborhood\_set$
13. **End For**
14. **End While**
15. **For** t = 1 to $no\_of\_clusters$ **do**
16. **For** i = 1 to n^t **do**
17. membership u_i is calculate via (6)
18. **End For**
19. **End For**
20. **For** t = 1 to $no\_of\_clusters$ **do**
21. $\hat{x}_t\,(k\mid k)\,\&\hat{p}_t\,(k\mid k)$ calculate based on (9) & (10)
22. **End For**

parameter is a strong point of proposed method against other approaches that require setting of many parameters. To fix the right values of this parameter, an exploration phase of trials and errors have been performed. Let assume that 3 sensors i, j, and k have sensed a target's signals and reported its track (position at specific point of time t) respectively as P_i, P_j, and P_k to FC. Let assume that after fusion, FC calculated target's position at time t as P. We found that, when the Eps value according to relation (12) is set to the maximum distance between reported target positions by sensed sensors and position of target reported by FC, FDBSC-TA is conducted to more accurate results.

$$Eps = \max_{l\in\{i,j,k\}} dist\{P, P_l\} \tag{12}$$

A. SCENARIO I

We considered an example with four targets with linear motion and five sensors [1]. Figure 1 demonstrates this scenario in which the lines indicate the placement of targets in the surveillance environment of sensors and the sensors overlapping. The models of motion and measurement of targets are defined by (2) and (3), so that the state transition matrices F and the nonlinear measurement matrices H are

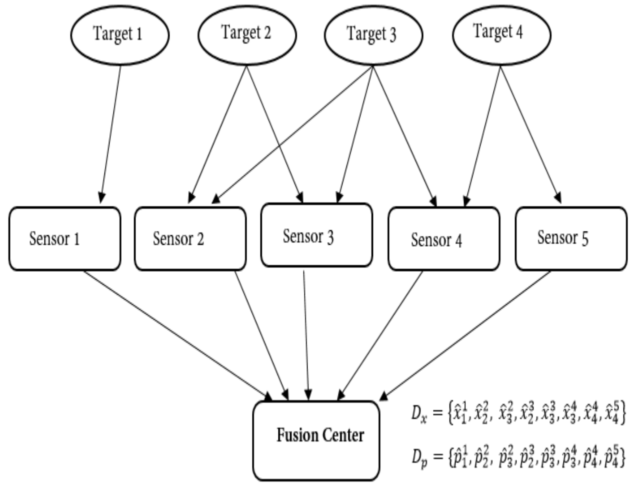

FIGURE 1. Four targets and five sensors in overlapping coverage scenario [1].

as follows [37]:

$$F = \begin{pmatrix} 1 & \delta & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \delta \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{13}$$

$$H(x(k)) = \begin{bmatrix} \sqrt{(x\,(k) - x_0)^2 + (y\,(k) - y_0)^2} \\ atan\frac{y(k)-y_0}{x(k)-x_0} \end{bmatrix} \tag{14}$$

The covariance matrices $Q_{2\times 2}$ is the system noise, which is assumed to be $Q_{ii} = (0.02^2)$ km^2 ($Q_{ij} = 0$, for $i \neq j$), and all the measurement noise are assumed $\sigma_r = 5$m and $\sigma_\theta = 0.1$ mrad. The detection probability of all sensors is assumed to be 0.95. Each sensor locally tracks targets in its surveillance environment based on FD-JPDAF and reports them to the FC. In addition, the bias of the sensors were considered zero in this scenario.

Figure 2 shows the actual path of targets motions. Table 2 presents the average RMSE of targets position from the local tracks, and tracks resulted from the combination in FC for FDBSC-TA, TFT, and MMSE. As observed, RMSE for target 1 is the same for all cases due to tracking by only sensor 1. Further, the RMSE of the track FC improved remarkably for other targets with respect to local tracking (the error rate has reduced by more than 60%). Comparing the results obtained from FDBSC-TA and FTF methods indicates the better performance and efficiency of the proposed method. The combination of tracks based on MMSE criteria yields better performance in comparison with other methods. In fact, as mentioned in Section 1, fuzzy-based methods such as FDBSC-TA and TFT are placed in suboptimal methods category with respect to MMSE criteria [1].

B. SCENARIO II

For a detailed review of efficiency of the proposed method, a scenario including three targets with constant motion is considered in a multi-sensor environment with three

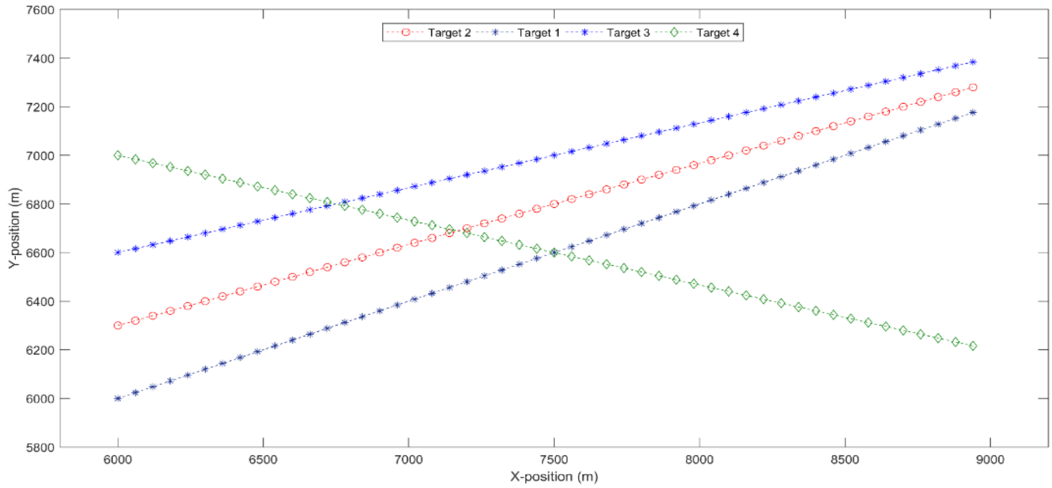

FIGURE 2. Targets trajectories in scenario I.

TABLE 2. Position RMSE of local and FC tracks (m/s) in scenario I.

<table>
<tr><th></th><th colspan="2">Target 1</th><th colspan="2">Target 2</th><th colspan="2">Target 3</th><th colspan="2">Target 4</th></tr>
<tr><td rowspan="3">Local Tracks</td><td rowspan="3">Sensor 1</td><td rowspan="3">21.74</td><td>Sensor 1</td><td>22.73</td><td>Sensor 2</td><td>21.17</td><td>Sensor 4</td><td>23.39</td></tr>
<tr><td rowspan="2">Sensor 2</td><td rowspan="2">22.94</td><td>Sensor 3</td><td>21.78</td><td rowspan="2">Sensor 5</td><td rowspan="2">23.81</td></tr>
<tr><td>Sensor 4</td><td>22.64</td></tr>
<tr><td>FTF</td><td colspan="2">21.74</td><td colspan="2">11.82</td><td colspan="2">11.32</td><td colspan="2">14.79</td></tr>
<tr><td>FDBSC-TA</td><td colspan="2">21.74</td><td colspan="2">10.25</td><td colspan="2">9.96</td><td colspan="2">12.54</td></tr>
<tr><td>MMSE</td><td colspan="2">21.74</td><td colspan="2">9.36</td><td colspan="2">9.07</td><td colspan="2">11.02</td></tr>
</table>

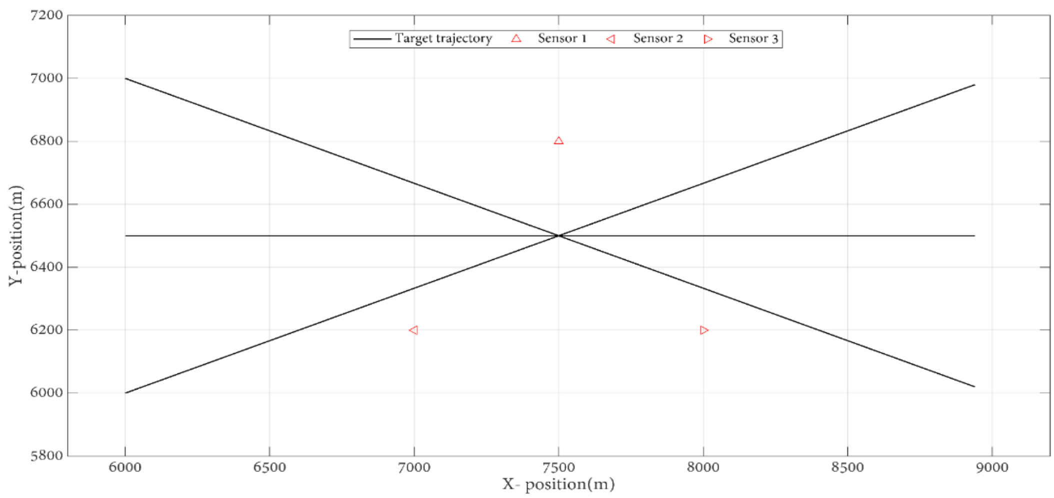

FIGURE 3. Target trajectories and sensors positions in scenario II.

complete-overlapping sensors. The initial state of targets was (6000m, 60 m/s, 6000m, 20 m/s), (6000m, 60 m/s, 6500m, 0 m/s) and (6000m, 60 m/s, 7000m, −20 m/s). The state transition matrix F, measurement matrix H, covariance matrixes $Q_{2\times 2}$ and measurement noise are similar to the scenario I. We would like to emphasize that all of the simulation parameters in these part are identical to parameters in scenario I.

Figure 3 exhibits the motion of targets and the position of sensors. The bias of sensors are equal to (0.4 km, 0.03 rad), (0.5 km, 0.08 rad), and (0.6 km, 0.04 rad) for

TABLE 3. The sensors biases estimates of the proposed method.

Parameter	True value (km)	Estimation (km)	Parameter	True value (rad)	Estimation (rad)
η_{r_1}	0.4	0.394	η_{θ_1}	0.03	0.0295
η_{r_2}	0.5	0.49	η_{θ_2}	0.08	0.0787
η_{r_3}	0.6	0.593	η_{θ_3}	0.04	0.0396

TABLE 4. Position RMSE of local and FC tracks (m/s) in scenario II.

		Target 1	Target 2	Target 3
Local Tracks	Sensor 1	23.79	23.12	23.92
	Sensor 2	24.63	24.06	24.02
	Sensor 3	23.72	22.97	23.13
FTF		13.14	12.77	12.94
FDBSC-TA		11.97	11.41	11.45
MMSE		8.92	8.27	9.58

sensors 1, 2, and 3, respectively. The probability of detecting all sensors was 0.95. Each sensor locally and independently processes the received measurements based on the FD-JPDAF method without registration and reports its estimates of tracks, then the FDBSC-TA performs the TTTA and TF tasks. Finally, the bias of sensors in the FC are corrected after estimating the target's state ($\hat{x}_t(k)$) based on Guo *et al.* [37] article.

$$\hat{\eta}_k^s = \frac{1}{n^s}\sum\nolimits_{i=1}^{n^s}\left(\hat{z}_{k,i}^s - h_s(\hat{x}_i(k))\right) \tag{15}$$

where n^s denote the number of tracks report by sensor s.

Table 3 represents the estimation of sensors bias. The numerical results show the low error of estimation. Table 4 clarifies the RMSE of targets position for local tracks, and tracks derived from the combination in FC for FDBSC-TA, TFT, and MMSE. By comparing the RMSE of local tracks, it can be observed that the tracks of the sensor 3 have the lowest error rate while the tracks of the sensor 2 have the highest error rate, which is due to the bias estimation error of these sensors.

In addition, comparing the results of local tracking and tracks derived from the combinations represent the improvement of results in tracks derived from the estimation by approximately 46%, 54%, and 65% for FTF, FDBSC-TA and MMSE, respectively. Moreover, the results of the FDBSC-TA and FTF methods represent an improvement of RMSE error in the proposed method by approximately 10%. As in the previous scenario, the error rate of FDBSC-TA and FTF methods are worse than that of MMSE, which is related to the sub-optimality of these methods according to the explanation of the previous section.

C. SCENARIO III

Two maneuvering crossing targets are considered in last scenario. The acceleration uses the additive term in the maneuvering model, which is given by:

$$x_j(k+1) = F_j(k)\,x_j(k) + C_j(k)\,u_j(k) + G_j(k)\,v_j(k) \tag{16}$$

By adding the acceleration term to the state equation, the MIE method [41] is used for local tracks estimation. The state transition matric F is similar to the previous example, where G and measurement matrix H are given by [36]:

$$G = \begin{pmatrix} \delta/2 & 1 & 0 & 0 \\ 0 & 0 & \delta/2 & 1 \end{pmatrix}^T \tag{17}$$

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \tag{18}$$

The matrix C in (16) is the same as G. The remaining parameters were set at the same values as in the previous scenario. The initial state vector and acceleration vector parameters for the entire simulation are given in Table 5. Figure 4 shows the actual path of targets motion and the position of sensors.

In this scenario, the average probability of correct association was employed as association performance criterion [7].

$$P_c = \frac{1}{MK}\sum\nolimits_{i=1}^{M}\sum\nolimits_{j=1}^{K}\frac{N_c^i(j)}{N_{public}(j)} \tag{19}$$

where N_{public} denote the total number of common targets, N_c^i denotes the number of tracks with the correct association at the i^{th} Monte-Carlo run, M is the number of Monte-Carlo runs, and K is the overall tracking time. Figures 5 and 6 show the comparison of the average probability of correct association for different angle biases and range biases, respectively.

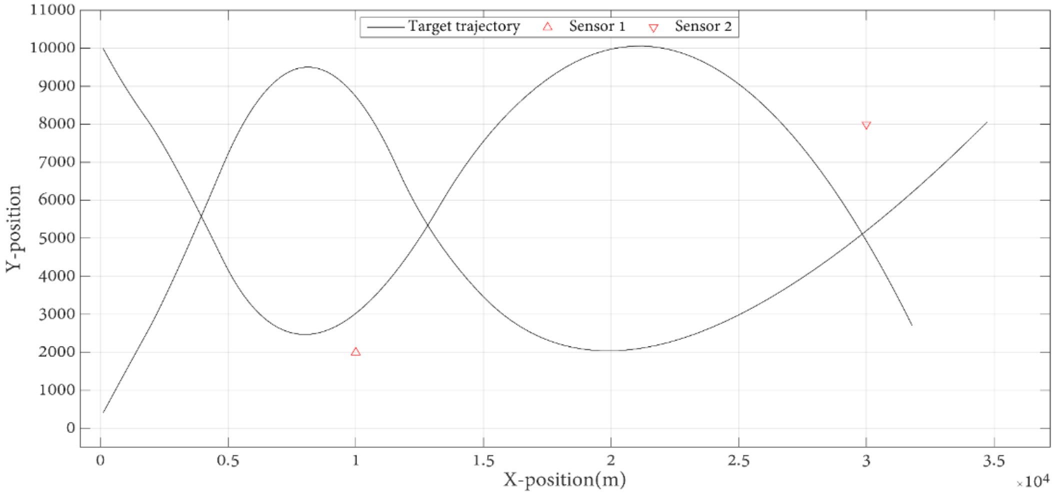

FIGURE 4. Targets trajectories and sensors positions in scenario III.

TABLE 5. Simulation parameters in maneuvering crossing targets.

Simulation	Initial position(m)	Initial Velocity(m/s)	Acceleration(m/s^2)				
			0-20s	21-40s	41-73s	74-85s	86-117s
Target 1	(100,1000)	(80,-100)	(0,0)	(5,-10)	(3,19)	(5,-15)	(0,-20)
Target 2	(100,400)	(80,100)	(0,0)	(5,10)	(0,-20)	(10,7)	(10,19)

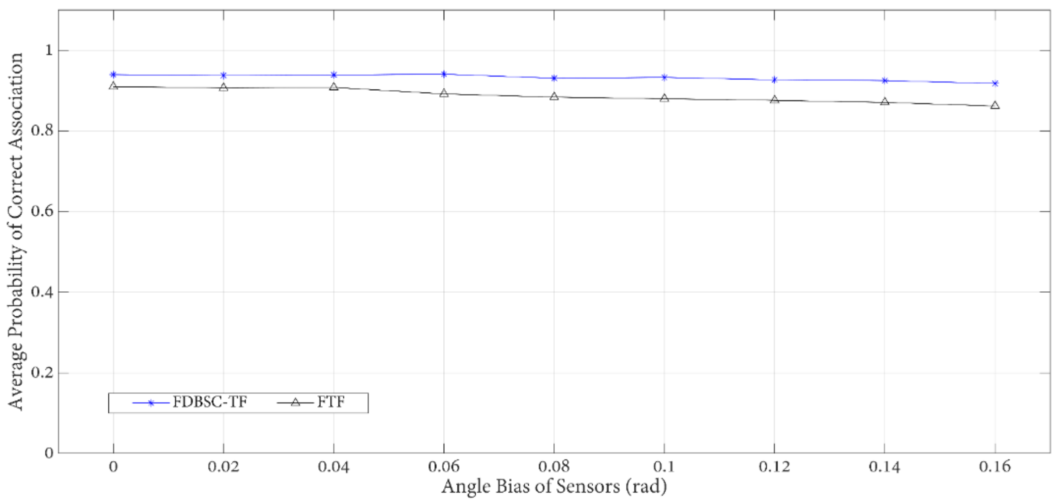

FIGURE 5. Average probability of correct association via different angle biases.

In Figure 5, the range biases of sensors (η_{r_1} and η_{r_2}) are set 0.5 km and the angle biases of sensors varies from 0 rad to 1.7 rad. Against, in Figure 6, the angle biases of sensors (η_{θ_1} and η_{θ_2}) are assumed fixed and set to 0.4 rad, and the range biases of sensors varies from 0 km to 2 km. It is observed from Figures 5 and 6 that increasing the biases of sensors leads to the decrease of the average probability of correct association. The proposed method has higher flexibility than the FTF, compared to increase of sensors biases.

In the second part of evaluating this scenario, the RMSE of targets position for local tracks and tracks derived from the combination in FC for FDBSC-TA, TFT, and MMSE are

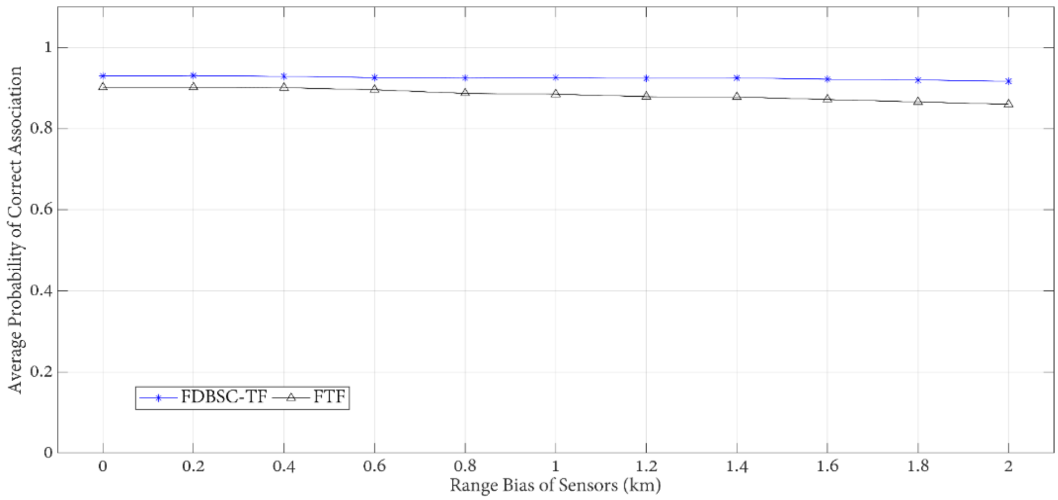

FIGURE 6. Average probability of correct association via different range biases.

TABLE 6. Position RMSE of local and FC tracks (m/s) in scenario III.

		Target 1	Target 2
Local Tracks	Sensor 1	284.61	263.13
	Sensor 2	267.29	253.65
FTF		136.47	132.96
FDBSC-TA		133.08	121.53
MMSE		92.34	87.48

illustrated in Table 6. Biases of sensors 1 and 2, respectively are considered (0.4 km, 0.03 rad) and (0.5 km, 0.08 rad) for simulation results of Table 6. By comparing results, it can be observed that the tracks of the sensor 2 have the lower error rate than the tracks of the sensor 1. Moreover, the results of the FDBSC-TA and FTF methods represent an improvement of RMSE error in the proposed method by approximately 3% and 8% for target 1 and target 2, respectively. Also, like the previous scenarios, the combination tracks of the MMSE have the lowest error rate.

VI. CONCLUSION

In this paper, a density-based clustering method for solving TTTA problem in distributed multi-sensor tracking systems is developed. In multi sensor tracking system, we faced with the problem of multiple tracks for a target that may be reported by different sensors. The proposed method employs the maximum entropy approach for determining the degree of fuzzy membership of duplicate tracks and subsequently combining a target related tracks. One advantage of proposed method is that it does not need to know the number of targets as priori. This reduces computational load and permits its use in real-time applications. Computational cost of proposed method in worst case scenario is $(T \times n^2)$. This enables us to use proposed method in real time applications. Furthermore, this approach was able to be integrated with other TF methods such as Dempster-Shafer or fuzzy-based approach after performing the TTTA process. The results of the simulations show the high performance of the proposed method for solving the TTTA and TF problems in dealing with different conditions such as sensors bias, the number of different targets, in complete or incomplete overlapping scenarios. As future works, it is planned to extend current proposed technique by tree-based structures such as R-tree, R*-tree or UB-tree.

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