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AN INTELLIGENT TECHNIQUE TO MULTI-SENSOR DATA FUSION IN TARGET TRACKING

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ABSTRACT

Combining the results of multiple sensors can provide more accurate information than using single sensor. In this paper, we develop fuzzy clustering approach to data association and track fusion in multi-sensor multi-target environment. The proposed approach uses the fuzzy clustering means algorithm to get the degree of membership of new tracks to existing tracks. Unlike existing approaches, in which the membership functions are fixed a priori (determined empirically), we generate optimal membership functions from the data using the fuzzy clustering means algorithm. More specifically, the values of the membership functions change according to the relative positions of the targets with respect to the sensors; this adaptation to the current state of the environment leads to far better/accurate results. Furthermore, our proposal can handle different types of information without excessive computation; indeed, it reduces considerably the computational complexity compared to existing schemes.

Keywords: *Distributed Sensors, Information Fusion, Intelligent Tracking, And Multi-Sensor- Multi-Target Tracking.*

1. INTRODUCTION

In a multi-sensor-multi-target (MSMT) environment, where each sensor processes its own observations and sends the resulting tracks to a data fusion center, the first step is to determine whether or not two or more tracks, coming from different sensor systems with different accuracies, represent the same target (track-to-track association "TTTA"). The next step is to combine the sensor tracks when it is determined that they indeed represent the same target (track fusion). Both problems arise when several sensors carry out surveillance over a common volume (overlapping sensor coverage). A survey of the current research in this area has been presented in [1-7, 37-39].

There are two approaches for fusion of multiple sensor data: measurement fusion and state vector fusion. In the first approach, the sensor measurements are combined [11] and an optimal estimate of the target state vector is obtained. Since this approach is optimal, it is theoretically superior. But for various reasons it may not be practical for field of implementation. This is so because the volume of sensor data to be transmitted to the fusion center from different stations could overwhelm the capacity of the existing data links among those stations. For this reason, state vector fusion is preferable for implementation in a variety of practical systems. In this approach, each sensor employs an estimator to extract a target track state vector and its associated covariance matrix from its respective sensor measurement, that are then transmitted over a data link to a fusion center. At the fusion center, track-to-track correlation and state vector fusion are performed to obtain a composite target state vector [19].

This paper proposes an intelligent method reduces the computationally complexity and achieves considerable performance improvement.

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The proposed method uses fuzzy clustering means (FCM) algorithm to reduce the number of target tracks by determining the degree of membership for each target track. The proposed method uses current sensor data and the known sensor resolutions for track-to-track association and the selection of the most accurate sensor for tracking fused targets. The obtained degrees of memberships are then compared to decide whether the state estimates (tracks) represent the same target or not. Results based on Monte Carlo simulations are presented. The proposed method is able to perform track correlation and fusion with a little prior knowledge. It can handle different types of information without excessive computation.

The remainder of this paper is organized as follows. Section 2 presents a brief overview of data association and fusion methods in MSMT tracking systems. Section 3 describes the fuzzy clustering means algorithm; we use this algorithm to develop our proposed approach. In Sections 4 and 5, we present the proposed fuzzy track-to- track association and fuzzy track fusion. Simulation results and discussion are presented in Section 6. Finally, Section 7 concludes the paper.

2. ASSOCIATION AND FUSION METHODS IN MSMT

Willner et al.[11] addressed the problem of track fusion (TF) of two track estimates assuming independent estimation errors. Bar-Shalom [7, 12] studied the TTTA and TF assuming that the estimation errors of different systems are correlated. The results show that taking into consideration the cross correlation between the two estimates reduces the estimation error [12-14]. The problem of TF of sensors with dissimilar accuracies is discussed in several papers [14-20]. The results show that under certain conditions the performance of the fused track may perform worse than the performance of the better quality sensor estimate. Saha et al. [21] reported that the performance of the fused estimate is marginally better than the better quality sensor estimate when the sensors are dissimilar (with different sensor accuracies). The best performance of the fused estimate is obtained when the two sensors are similar. The performance of the fused track is worse than the performance of the better quality estimate when the two sensor noise variances vary widely [13, 19]. In this case, it is recommended to adopt the estimate of the better quality sensor. In general, the computational cost in generating the optimal solutions to the problems of TTTA and TF is usually excessive and infeasible for real-time surveillance systems. Furthermore, all these approaches assume prior knowledge of the signal environment, which is limited in practice.

Unlike the optimal solutions, the suboptimal solutions provide approximate solutions to the problems of TTTA and TF. The approximate solutions are based on neural network and fuzzy logic techniques [22-32]. The major drawbacks of the neural network implementations are that they require unreasonable numbers of neurons and require training with a very large set of tracks [31].

Several studies have been done in the application of fuzzy techniques to TTTA and TF. Application of the fuzzy logic to the data association problem provides an approximate solution, and the results are subjected to the number of input variables, number of linguistic variables, the membership function, and the accuracy of the rules. Singh and Bailey [23] developed a first fuzzy logic approach for the data association problem; it can be applied to solve data association problems in MSMT tracking. In their approach, the distance measure has not been used in the usual manner, but the fuzzy logic technique has fuzzified the distance measures for use by the fuzzy knowledge-base (IF-THEN rules). The major advantage of their approach is its ability to handle different types of information. Unfortunately, the extension of their approach to the case of more than three or four targets is computationally unfeasible due to the large number of rules. Furthermore, as the system complexity increases, it becomes difficult to determine the right set of rules and membership functions to describe the system behavior.

In fuzzy clustering, each data point can be associated with more than one cluster with some degree of membership. The membership degrees are determined in a way to minimize or maximize a function. Recently, fuzzy clustering has been applied to data association and target identification. Wide [26] developed a fuzzy technique for classification of measurements in different known quality profiles. In his approach, the quality profiles and the sensor measurements are fuzzified using arbitrary (triangular) membership functions. The resulting fuzzy measurements and fuzzy profiles are compared to select the most representative profile for each measurement. Hossam et al. [22] developed a fuzzy approach for solving the data association problem in target tracking. Their approach selects the true measurement from many received measurements for a single target. A fuzzy membership function is assigned to each attribute of the measurement vector. The resulting fuzzy measurements are then defuzzified such that the measurement with the maximum degree of

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membership is chosen as the true measurement. Smith [28] developed a fuzzy logic association approach for TTTA in MSMT environments. He uses the fuzzy clustering algorithm to determine the grades of membership of all observations to a known number of targets. His approach requires initialization of either the prototype values or the grade of memberships.

In the fuzzy track-to-track and track fusion approaches we propose in this paper, the optimal membership functions are generated from the data using the fuzzy clustering means algorithm; they are not fixed a priori (the case of existing approaches). The degrees of membership of the sensor resolutions are adapted in response to the received measurements. More specifically, the values of the membership functions are changed according to the relative positions of the targets with respect to the sensors. The adaptation of the proposed approaches to the current state of the environment produces high accuracy results. Also the computational complexity is reduced by a factor of n_a, where n_a is the total number of attributes; indeed the proposed approach assigns one degree of membership to each report rather than assigning one degree of membership for each attribute (the case of existing approaches); thus, the number of comparisons does not grow with the number of attributes. This also allows reducing the sensitivity of the final decision to individual attribute fluctuations.

3. FUZZY CLUSTERING MEANS ALGORITHM.

The goal of any fuzzy clustering algorithm is to classify the data into a number of clusters (groups). The clustering algorithms produce a degree of membership for each data point in each cluster. Given a number of data points, it is required to group (cluster) the data into clusters according to some similarity measure. Let c be an integer which represents the number of clusters with $2 \leq c \leq n$, where n is the number of data points. Let us define U as partition matrix of elements μ_{ij} (i=1,2,…, c , j=1,2,…,n) which represents the degree of membership of data points j in fuzzy cluster i, such that

$$\mu_{ij} \in [0,1] \quad 1 \leq i \leq c, \quad 1 \leq j \leq n \qquad (3.1)$$

$$\sum_{i=1}^{c} \mu_{ij} = 1 \qquad \forall j \qquad (3.2)$$

$$0 < \sum_{j=1}^{n} \mu_{ij} < n \qquad \forall i \qquad (3.3)$$

Let J_m be the sum of the squared errors weighted by the m^{th} power of the corresponding degree of membership.

$$J_m(u,v) = \sum_{j=1}^{n}\sum_{i=1}^{c} (\mu_{ij})^m (d_{ij})^2 \qquad (3.4)$$

where

$$(d_{ij})^2 = // z_j - v_i //^2 \qquad (3.5)$$

Z_j is a data point, v_i is a cluster center, and // // is the induced norm, m is a real number Є [1,∞) called the fuzzification constant (or weighting exponent). The degree of membership will be established by minimizing the sum of the squared errors weighted by the corresponding m^{th} power of the degree of membership. The goal of fuzzy clustering algorithm is to determine the optimum degree of membership μ_{ij} and the optimum fuzzy cluster centers v_i such that the sum of the squared errors J_m is minimum. The results of the resolution of this optimization problem are [32] :

$$\mu_{ij} = \frac{1}{[\sum_{k=1}^{c} (d_{ij} / d_{kj})^{2/(m-1)}]} \qquad \forall i, j \qquad (3.6)$$

$$v_i = \frac{\sum_{j=1}^{n} (u_{ij})^m x_j}{\sum_{j=1}^{n} (u_{ij})^m} \qquad \forall i \qquad (3.7)$$

where Equation (3.6) is valid for a fixed v_i (i= 1,2,…,c), and Equation (3.7) is valid for a fixed U. The fuzzy c–means clustering algorithm or the Picard algorithm is guaranteed to converge to a local minimum [35].

It is worth noting that the fuzzification constant m plays a key role in reducing the influence of noise when computing the degrees of membership (3.6) and the cluster centers (3.7); it reduces the influence (impact) of a small μ_{ij} (for data that are far away from the cluster centers) compared to a large μ_{ij} (for data that are close to the cluster centers). When m increases, its influence/impact becomes stronger [36].

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4. PROPOSED FUZZY TRACK-TO-TRACK ASSOCIATION (FTTA)

Let us assume, for simplicity, that we have two tracks coming from two different sensors

$$T_i = \begin{pmatrix} attribute & 1 \\ attribute & 2 \\ \dots\dots\dots & \dots\dots \\ \dots\dots\dots & \dots\dots \\ \dots\dots\dots & \dots\dots \\ attribute & n_a \end{pmatrix},i=1,2$$

(4.1)

with corresponding resolutions

$$\Delta_i = \begin{pmatrix} resolution\ of\ attribute\ 1 \\ resolution\ of\ attribute\ 2 \\ \dots\dots\dots \\ \dots\dots\dots \\ \dots\dots\dots \\ resolution\ of\ attribute\ n_a \end{pmatrix},i=1,2 \qquad (4.2)$$

where n_a is the total number of attributes. The first sensor (S1) is assumed to be more accurate than the second sensor (S2) i.e.,

$$\Delta_1(a) < \Delta_2(a) \ \ \forall a = 1,2,\dots,n_a \qquad (4.3)$$

The attribute may be range, bearing, or speed; it is used to decide whether or not two given tracks represent the same target.

We consider this problem as a binary hypothesis testing for two local sensors. The two hypotheses are:

The two tracks represent the same target (H_1)

The two tracks represent different targets (H_0), i.e.,

$$H = \begin{cases} 1, & H_1 \\ 0 & H_0 \end{cases} \qquad (4.4)$$

The case of two sensors observing one target, where the true hypothesis is H_1 is shown in Figure 1 and the case of two sensors observing two targets, where the true hypothesis is H_0 is shown in Figure 2.

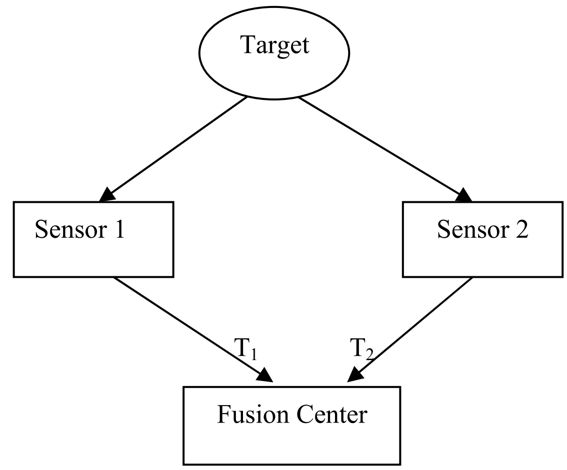

Figure 1 Two Sensors Observing One Target in Overlapping Coverage (H_1)

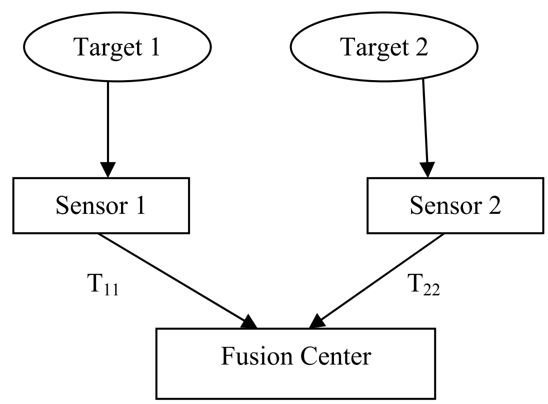

Figure 2 Two Sensors Observing Two Targets in Overlapping Coverage (H_0)

The two-track attribute difference $|T_2 - T_1|$ can be compared with either the resolution of sensor 1 (Δ_1) or the resolution of sensor 2 (Δ_2).

It is required to utilize the FCM to match our problem. Let us define the comparison terms as distances:

$$d_{ij} = \begin{cases} \|T_j - T_i\|, if & i \neq j \\ \|\Delta_i\|, \quad if & i = j \end{cases} \qquad (4.5)$$

where $\| \ \|$ is the induced norm. Thus, we obtain the following distance matrix:

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$$d_{11} = \sqrt{\Delta_1^{'}\Delta_1} \quad (4.6)$$

$$d_{12} = \sqrt{(T_2 - T_1)^{'}(T_2 - T_1)} \quad (4.7)$$

$$d_{21} = \sqrt{(T_1 - T_2)^{'}(T_1 - T_2)} = d_{12} \quad (4.8)$$

$$d_{22} = \sqrt{\Delta_2^{'}\Delta_2} \quad (4.9)$$

The similarity measures between the elements of $\{d_{ij}\}$, i=1,2 and j=1,2, can be determined as the optimum degrees of membership using the fuzzy clustering means algorithm FCM (see Equation (3.6)). The result is as follows:

$$\mu_{11} = \frac{(1/\Delta_1^{'}\Delta_1)^{\frac{1}{m-1}}}{(1/\Delta_1^{'}\Delta_1)^{\frac{1}{m-1}} + (1/(T_1 - T_2)^{'}(T_1 - T_2))^{\frac{1}{m-1}}} \quad (4.10)$$

$$\mu_{12} = \frac{(1/(T_1 - T_2)^{'}(T_1 - T_2))^{\frac{1}{m-1}}}{(1/\Delta_2^{'}\Delta_2)^{\frac{1}{m-1}} + (1/(T_2 - T_1)^{'}(T_2 - T_1))^{\frac{1}{m-1}}} \quad (4.11)$$

$$\mu_{21} = \frac{(1/(T_2 - T_1)^{'}(T_2 - T_1))^{\frac{1}{m-1}}}{(1/\Delta_1^{'}\Delta_1)^{\frac{1}{m-1}} + (1/(T_1 - T_2)^{'}(T_1 - T_2))^{\frac{1}{m-1}}} \quad (4.12)$$

$$\mu_{22} = \frac{(1/\Delta_2^{'}\Delta_2)^{\frac{1}{m-1}}}{(1/\Delta_2^{'}\Delta_2)^{\frac{1}{m-1}} + (1/(T_2 - T_1)^{'}(T_2 - T_1))^{\frac{1}{m-1}}} \quad (4.13)$$

The equations 4.10-4.13 can be written in a matrix form as follows:

$$\mu = \begin{pmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{pmatrix} \quad (4.14)$$

In this formulation, μ_{ii} represents the degree of membership of the resolution of sensor i (i=1,2) and μ_{ij} represents the degree of membership of the difference between two tracks T_i and T_j with respect to the resolution of sensor j (the degree of similarity between a pair of tracks).

The global association decision (D_g) is always based on the least accurate sensor (sensor 2). In this case, we have

$$D_g = \begin{cases} 1 & \text{if } \mu_{12} > \mu_{22} \\ 0 & \text{if } \mu_{12} < \mu_{22} \end{cases} \quad (4.15)$$

The correlation between the two reports T_1 and T_2 can then be defined as follows:

$$CORR\ (1,2) = \begin{cases} 1 & \text{if } D_g = 1 \ (\text{same tracks}) \\ 0 & \text{if } D_g = 0 \ (\text{different tracks}) \end{cases} \quad (4.16)$$

The proposed track-to-track fuzzy association approach can be easily extended to the case of n_r reports obtained from more than two sensors observing multiple targets.

5. PROPOSED FUZZY TRACK FUSION

Once two or more tracks have been associated to the same target, the next step is to combine them into a single track. This can be done either by adopting the superior (best) track, or by fusing the tracks into a single one. It will be shown that under certain conditions the fused track may yield a worse estimate than the superior track. In this case, track fusion is not recommended.

The superior track can be selected according to the characteristics of the sensors in terms of sensor resolutions. If the sensors have the same resolution, the superior track is chosen according to the operating conditions, such as the relative distance to the target. The smaller the relative distance the more accurate is the sensor track estimate. In our proposed approach, the superior track is determined automatically from the data. The superior track is the track that has maximum degree of membership in the diagonal elements of the similarity matrix (see Equation (4.14)).

For better understanding, let us consider the case where it has been decided that s tracks are the same (represent the same target i); this means

$$CORR(k_1,i)=CORR(k_2,i)=\ldots=CORR(k_s,i)=1 \quad (5.1)$$

The superior track is:

$$T_{sup}=T_{Ksup} \quad (5.2)$$

where

$$K_{sup}=Max_k\ \{\mu_{kk}\}\ ,\ k=k_1, k_2, \ldots,k_s \quad (5.3)$$

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In this case, the superior track is determined according to the sensor resolutions as well as the similarity between all the estimated tracks.

In the case of track fusion (TF), we can combine the tracks according to the corresponding degrees of membership. Thus, the fused track estimate can be defined as:

$$TF = \frac{\sum_{k=1}^{k=r} T_{ik} \; \mu_{kk}}{\sum_{k=1}^{k=r} \mu_{kk}} \qquad (5.4)$$

Where r is the number of tracks representing the same target i. The proposed fuzzy track-to-track association and track fusion approaches are illustrated in the block diagram of Figure 3.

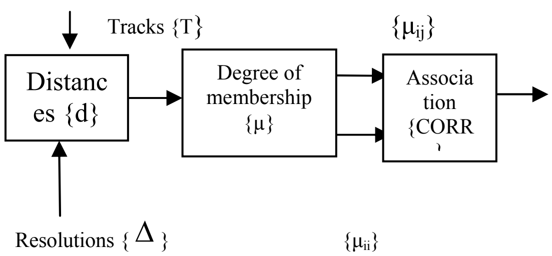

Figure 3 Proposed Fuzzy Track-to-Track Association and Track Fusion Approach.

6. SIMULATION RESULTS

We consider the scenario of three targets moving with different speeds and different accelerations as follows:

- Target 1 (tg 1) moves horizontally with constant speed during t=60 sec (total simulation period)
- Target 2 (tg 2) moves diagonally with constant speed in x-y direction.
- Target 3 (tg 3) moves with constant speed and acceleration until t= 30sec, when it maneuvers highly in x and lowly in y direction with acceleration inputs (10g, 2g) until t=40sec then, it makes another high maneuver in x and y directions with acceleration inputs (10g, 12g) until t=45 sec, then it moves with constant speed until t= 60 sec. This scenario is depicted in Figure 4.

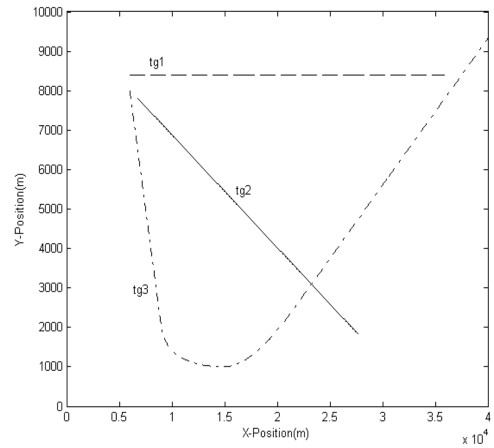

Figure 4 Actual Target Trajectories

We assume the test scenario of the true targets with the initial positions and velocities as shown in Table1.

Table1: Initial Positions and Velocities of Targets

target	X(m)	V_x(m/s)	Y(m)	V_y(m/s)
1	6000	500	8400	0
2	6800	350	7800	-100
3	6000	100	8000	-200

The targets observed by four sensors in overlapping coverage are shown in Figure 5 where:

(1)Target 1 is only detected by sensor 1. (Sensor observes only one target).

(2)Target 2 is detected by sensor 2 and sensor 3. (Target is detected by two sensors).

(3)Target 3 is detected by sensor 2, sensor 3 and sensor 4 (Target is detected by three sensors). The lines in Figure 5 indicate which sensors see which targets. The four sensors send six reports (T_{ij}) to the data fusion center, where T_{ij} represents the report from sensor j due to detecting target i. Each report represents the x and y positions of the targets.

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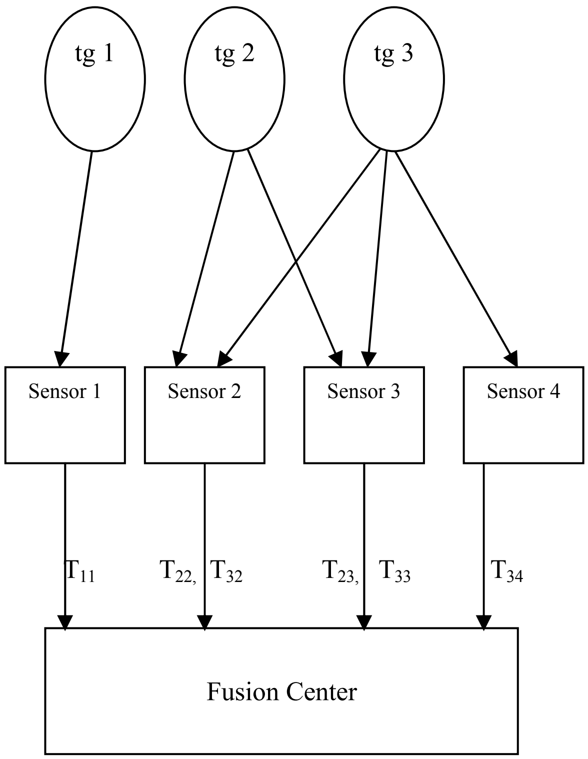

Figure 5 A Scenario of three Targets Observed by four Sensors

The targets motion model is assumed to be:

$$X(k+1) = F\,X(k) + BG(k) \tag{6.1}$$

where F is the state transition matrix given by:

$$F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6.2}$$

where T is the sampling interval; T=0.1sec in our simulations.

The 4x1 state vector X(k) contains the x and y target positions and velocities (see Equation 6.3). B represents the input matrix (see Equation 6.4) while G(k) represents the acceleration input vector of the maneuvering target at time k (see Equation 6.5).

$$X(k) = [x(k) \quad v_x(k) \quad y(k) \quad v_y(k)]' \tag{6.3}$$

$$B = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix} \tag{6.4}$$

$$G(k) = \begin{bmatrix} g_x(k) \\ g_y(k) \end{bmatrix} \tag{6.5}$$

The measurements are the x and y target positions given by:

$$Z(k) = H\,X(k) + V(k), \tag{6.6}$$

Where Z(k) is the measurement vector and H is a fixed matrix (see Equation 6.7).

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{6.7}$$

Measurements are affected by noise which is modeled as Gaussian, zero mean, with a certain standard deviation. The noise sequence V(k) has a covariance matrix R_k

$$R_k = \begin{bmatrix} \sigma_{ij}^2 & 0 \\ 0 & \sigma_{ij}^2 \end{bmatrix} \tag{6.8}$$

where σ_{ij}^2 represents the variance of the measurements error due to observing target i by sensor j.

The values of noise uncertainties (in meters) are taken in two cases: (1) The sensors are similar (sensors' resolutions are equal); see Table 2 for details; and (2) The sensors are dissimilar (sensors' resolutions are different); see Table 3 for details.

Table 2: Case 1. The Values of Noise Uncertainties in (meters)

σ_{11}	σ_{22}	σ_{32}	σ_{23}	σ_{33}	σ_{34}
100	100	100	100	100	100

Table 3: Case 2. The Values of Noise Uncertainties in (meters)

σ_{11}	σ_{22}	σ_{32}	σ_{23}	σ_{33}	σ_{34}
40	50	50	150	150	200

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The sensor resolutions are defined in terms of the noise standard deviation for each sensor assuming a common standard deviation in both x and y positions.

The root mean square error (RMSE) is defined as follows:

$$RMSE = \sqrt{(x_{true} - \hat{x})^2 + (y_{true} - \hat{y})^2} \quad (6.9)$$

where x_{true} and y_{true} are the true target trajectory while $\hat{x}$ *and* $\hat{y}$ are the kalman estimate target trajectories

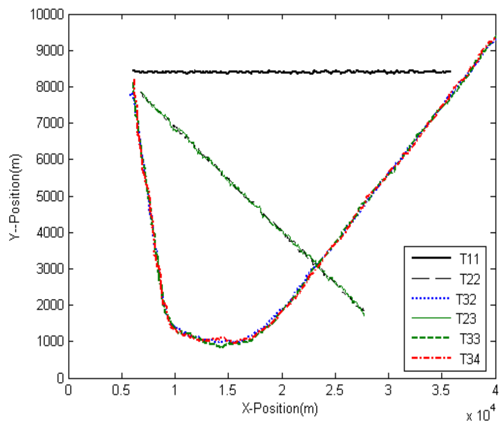

Figure 6 Tracks before fusion.

The fusion center is responsible for processing all of the reported tracks and fusing the redundant tracks into a single set of tracks. The displayed tracks before fusion are shown in Figure 6.

The proposed fuzzy track-to-track association approach successfully associates all the reported tracks and displays the right number of reports. The resulting correlation matrix, after applying correlation rule (4.16), is shown in Table 4. All the redundant tracks are fused and all the superior tracks (better quality sensor tracks) are correctly determined.

In the case where target 2 is detected by two different sensors (i.e., sensor 2 and sensor 3) two tracks, representing target 2, are reported to the data fusion center, which are T_{22} and T_{23}. The data fusion center can either adopt the superior of the two tracks or fuse them into a global estimate. Using the proposed approaches, we decide that the T_{22} is the superior track i.e., the track which is sent by sensor 2. Let us recall that the sensor 2 has the best resolution of the sensors which observe target 2.

	(T_{11})	(T_{22})	(T_{32})	(T_{23})	(T_{33})	(T_{34})
(T_{11})	0	0	0	0	0	0
(T_{22})	0	0	0	1	0	0
(T_{32})	0	0	0	0	1	1
(T_{23})	0	1	0	0	0	0
(T_{33})	0	0	1	0	0	1
(T_{34})	0	0	1	0	1	0

Table 4: Correlation Matrix

In the case where target 3 is detected by three different sensors (i.e., sensor 2, sensor 3, and sensor 4) three tracks, representing target 3, are reported to the data fusion center, which are T_{32}, T_{33}, and T_{34}. The data fusion center can either adopt the superior of the three tracks or fuse them into a global estimate. Using our approach, we can decide that the T_{32} is the superior track i.e., the track which is sent by sensor 2. Let us remind that the sensor 2 has the best resolution of the sensors which observe target 3.

Upon deciding that the tracks represent the same target (track fusion), we can combine the tracks according to the corresponding degrees of membership. In this way, the fused track with respect to target 2 and target 3 can be determined from Equation (5.4).

To measure the performance of the proposed fuzzy fused track, we compare the results of the fuzzy fused track of target 2 and target 3 with convex combination (CC) method [33] and simple fusion method (SF) [34]. The fused tracks of target 2 and target 3 by three different methods are shown in Figure 7 and Figure 8 respectively.

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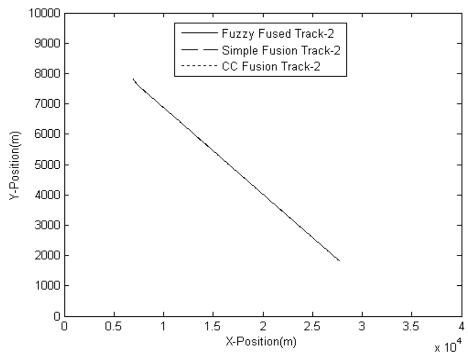

Figure 7 Target 2: Fused tracks

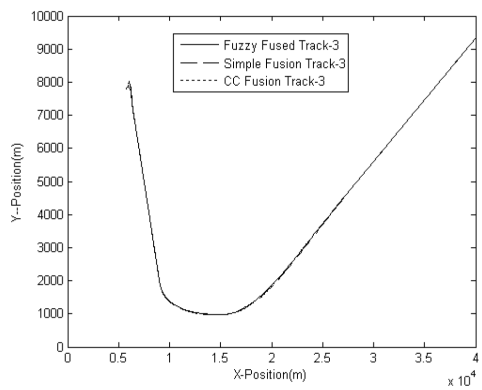

Figure 8 Target 3: Fused tracks

The comparisons of the root mean square error of the three different methods and also with the superior track with respect to target 2 in case of similar sensors (case 1) and dissimilar sensors (case 2) are depicted in Figure 9 and Figure 10 respectively. The comparisons of the root mean square error of the three different methods and also with the superior track with respect to target 3 in case of similar sensors (case1) and dissimilar sensors (case 2) are depicted in Figure 11 and Figure 12 respectively.

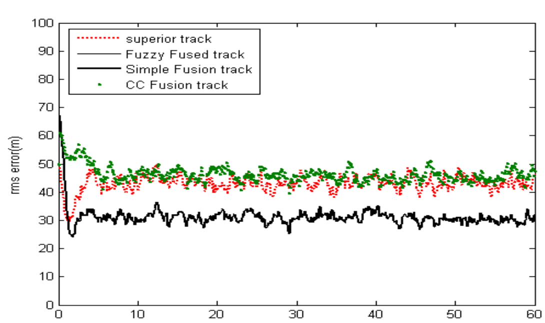

Figure 9 RMSE of Target 2 in Case 1

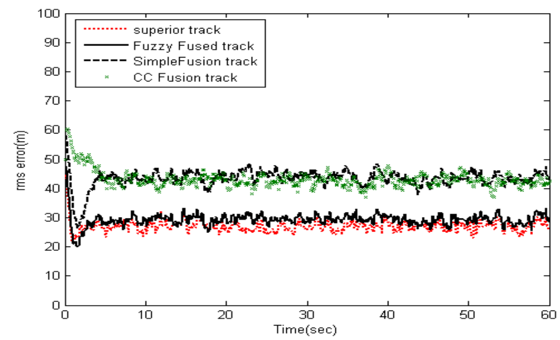

Figure 10 RMSE of Target 2 in Case 2

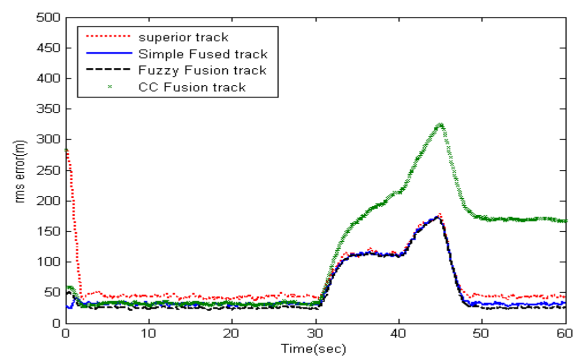

Figure 11 RMSE of Target 3 in Case 1

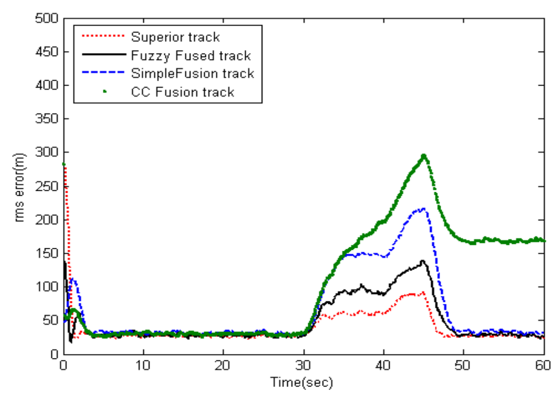

Figure 12 RMSE of Target 3 in Case 2

The quantitative comparison (given by the value of mean of RMSE (m)) between all the 3 methods with respect to target 2 and target 3 in case 1 (similar sensors) and in case 2 (dissimilar sensors), in 200 Monte Carlo simulations are given in Table 5.

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Table 5: Quantitative Comparison.

	CASE 1 (SIMILAR SENSORS)		CASE 2 (DISSIMILAR SENSORS)	
	Target 2	Target 3	Target 2	Target 3
Superior track	43.05	69.14	**23.09**	**39.92**
Fuzzy Fusion	**31.17**	**54.34**	25.02	48.55
Simple Fusion	31.17	56.75	32.24	67.15
CC Fusion	46.27	111.32	42.64	105.76

The results show that the performance of the proposed Fuzzy fused track is better than the performance of all other fusion algorithms in case 1 with respect to target 2 and target 3 when the sensors have similar resolutions; let us note that the simple fusion method gives the same result as fuzzy fusion.

When the difference in sensor resolutions is large (case 2), the performance of the fused track is worse than the performance of the superior track especially with respect to target 3. In this case, fusion of sensors track is not recommended and adopting the superior track is recommended.

Also note that in Figure 11 and Figure 12, the RMSE increases during the maneuvering period (30-45 sec) with respect to target 3 due to Kalman estimate error and by increasing the covariance of the Kalman estimate, we could get a definite RMSE error during that period and thereby better results.

7. CONCLUSION

Track-to-track association and track fusion in multisensor-multitarget with overlapping sensor coverage have been considered in this paper. A fuzzy clustering technique employing track-to-track association and track fusion have been proposed.

In general, track fusion would yield the best estimate when the sensors have the same resolutions; however, when the sensor resolutions vary widely (large difference in sensor resolutions), it is better to adopt the superior track rather than fusing the tracks. The proposed fuzzy track-to-track association and track fusion approach has several advantages over existing approaches:

- Unlike, all fuzzy track-to- track association and track fusion approaches in which the membership functions are fixed a priori, the optimal membership functions, using the proposed approach are generated from the data using the fuzzy clustering means algorithm, and they are not fixed a priori. As a consequence, the degrees of membership of the sensor resolutions are impacted by the received measurements. This means that the values of the membership functions are changed according to the relative positions of the targets with respect to the sensors; thus, the proposed approach adapts to the current state of the environment and thus produces better/accurate results.
- It reduces the computational complexity with a factor of n_a, where n_a is the total number of attributes. More specifically, the proposed approach assigns only one degree of membership to each report rather than assigning one degree of membership for each attribute (the case of existing approaches); the number of comparisons does not grow with the number of attributes).
- It avoids conflict situations where, for example, track A is associated with track B, track B is associated with track C, but track A is not associated with track C. This is achieved since the proposed approach determines the similarity between tracks by considering all tracks at once.
- It determines the superior track automatically based on the values of the sensor resolutions. The superior track is the track that has maximum degree of membership in the diagonal elements of the similarity matrix. Thus, it is easier and fast to determine the superior track.

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