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A New Nearest Neighbors Data Association Approach Based on Fuzzy Density Clustering

M. Nazari[1], M. M. AlyanNezhadi[1]*, S. M. R. Hashemi[2], S. M. Mirrezaei[3]

[1] Department of Computer Science, University of Science and Technology of Mazandaran, Behshahr, Iran
[2] Faculty of Computer Engineering, Shahrood University of Technology, Shahrood, Iran
3 Faculty of Electrical Engineering, Shahrood University of Technology, Shahrood, Iran

ABSTRACT: The problem of valid measurement's associations with true targets called "data association" is an essential challenge in multi-target tracking. Previous works often use the nearest neighbor or all neighbor approaches for updating the position of the targets, which are unsuccessful in complex environments and real-time applications, respectively. This paper provides a novel and effective solution to the data association problem in multi-target tracking, offering promising advancements in heavily cluttered environments. The proposed method uses important measurements that are determined based on fuzzy membership degrees. We selected and used valid measurements with a high fuzzy membership degree for updating the position of the targets. In this paper, we used two approaches for the selection of important measurements. The first strategy selects the k measurements with the highest degree of membership among the valid measurements. A second strategy is to give up measurements with very low membership degrees. The ability to solve the data association problem for both approaches under different levels of selecting measurements is evaluated. The proposed method is examined under two scenarios: linear crossing and maneuvering targets. The results show that the proposed technique performs better than FNN, JPDAF, MEF-JPDAF, and Fuzzy-GA methods based on the RMSE criterion.

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1- Introduction

The aim of tracking systems is the estimation and prediction of the target state [1–6]to mitigate the clutter and jamming effect. A waveform is selected based on Cramer--Rao lower bound (CRLB. The tracking filter, data association (DA) process, and gating technique are the main components of tracking systems. Recursive Bayesian filters are usually employed as tracking filters that consist of prediction and updating steps [7–9]for situations where the target's physical size exceeds one sensor resolution cell or the transmission and received signals have multi-path propagations, one target generates multiple detections which terms the multiple-detection problem. The multiple-detection multiple-target tracking algorithms usually suffered from an intractable computational load and could not operate in real time when multiple targets are closely spaced or too many detections are generated. In addition, automatic track initialization technique in cluttered environments brings in the presences of both true and false tracks that false track discrimination is required. These two terms are critical for real tracking systems but largely neglected by the published papers for the multiple-detection problem. In this paper, the authors propose an algorithm, called the Multiple-detection Iterative Joint Integrated Probabilistic Data Association (MD-iJIPDA. At the first step of the tracking process, the target's state is predicted by the tracking filter. Next, after receiving measurements, the gating technique is used to determine valid measurements. Then, associating valid measurements with existing tracks is done through the DA process. Finally, the target's state is updated based on associated measurements. In dense environments, "clutter" or false alarms exist alongside real measurements and cause uncertainty about measurement sources. So, the gating technique is employed before DA to eliminate false alarms and to determine valid measurements. In this sense, we can say that DA is highly coupled with the determination of valid measurement [10–13].

Generally, DA methods are divided into two groups 1) nearest neighbor (NN) which uses the nearest measurement to the predicted position of targets, and 2) all neighbors (AN) which uses all valid measurements for updating the position of targets [11, 12, 14, 15]. The quality of the DA-based NN approach despite its simplicity, decreases as the false alarm rate increases or as targets get closer and cross. In contrast, AN leads to the complexity of tracking systems in real-time applications.

In recent decades, highly efficient DA methods were presented. Multi-hypothesis tracker (MHT) and joint probabilistic data association (JPDA) methods are efficient solutions for the DA problem in multi-target tracking systems [3, 9, 16–18]. These techniques use all valid measurements determined by the validation gate and work based on the AN approach. However, both of them have significant

*Corresponding author's email: alyan.nezhadi@gmail.com

computational complexity. An improved JPDA for tracking multiple maneuvering targets in cluttered environments with uncertain measurement noises and uncertain target dynamic models is developed by Fan et al. [14]. Their method has been combined with a fuzzy recursive least squares filter. Gorji et al.[18] have applied JPDA to tracking multiple mobile targets, which has been combined with a particle filter.

Generally, creating an optimal solution to the DA problem for tracking multiple targets in cluttered environments is usually costly [12, 19]. In consequence, soft computing-based DA techniques have been interesting. Whereas, soft computing-based DA methods are a suboptimal technique for DA problems that are classified into 1) fuzzy logic, 2) artificial neural networks, and 3) evolutionary algorithms [8, 9, 12, 20,21]. Due to the need for many neurons and training time, artificial neural network-based DA techniques are not welcome. In consequence, fuzzy-logic-based DA methods, especially fuzzy clustering-based DA techniques are interested in solving DA problems in real-time applications. In fuzzy-clustering-based DA methods, the fuzzy membership degree of valid measurements is used for updating the phase of the tracking filter. The main difference between fuzzy clustering DA methods is in the determination of fuzzy membership degree. Fuzzy C-means (FCM) clustering, fuzzy clustering based on maximum entropy, and intuitionistic fuzzy clustering are the main approaches that are used as fuzzy clustering for solving DA problems [22–28].

Liangqun et al. [22] developed the first DA method based on maximum entropy fuzzy clustering for tracking multiple targets in cluttered environments. Their approach reconstructs the joint association probabilities based on enhancement revision of maximum entropy fuzzy clustering. The combination of the DA technique based on maximum entropy Gaussian particle filter and fuzzy clustering is proposed by Zhang et al.[24]. In Ref. [26], a novel bearings-only algorithm is designed for tracking multiple maneuvering targets. Liangqun and Wei-xin [26] have suggested a DA algorithm based on intuitionistic fuzzy clustering. Also, for handling the uncertainty of measurement, two new weight assignment approaches are presented. Aziz [11] has suggested a new DA based on FCM clustering. The proposed method is based on the NN approach, in which the measurements with a maximum degree are used for updating the phase of the tracking filter. A hybrid DA method based on evolutionary and FCM clustering is suggested by Satapathi and Srihari [12]. Their DA techniques used of genetic algorithm and particle swarm optimization to overcome the local minima problem by FCM clustering. However, the need for evolutionary algorithms for iterations leads that this method dose not unusable in real-time applications [12]. An intuitionistic fuzzy model was created by Zhang et al. [29] for data association in multi-target dense clutter tracking. In their approach, intuitionistic C-means clustering and maximum intuitionistic entropy are used for model training, and handling of uncertainty between targets and measurements, respectively. A fuzzy C-means clustering strategy has been proposed by Wang and Zhang [30] to improve target number estimation in PHD filter tracking. In their approach, measurement clustering compensates for tracking losses in situations with high noise and clutter.

As mentioned above, the DA process is highly coupled with gating. All techniques for solving DA problems are working based on either the NN approach or AN approach, which fails in environments with a high clutter rate and leads to the complexity of tracking systems in real-time applications. Consequently, the necessity for a data association solution is required that have the following conditions: 1) independent from the gating results and 2) solving the DA problem based on the new approach which uses measurements with the highest fuzzy membership degree. Using important measurements increases efficiency in environments with a high clutter rate and causes the simplicity of tracking systems in real-time applications.

A density-based fuzzy clustering technique for solving the multiple targets DA problem is presented in this study, which works differently from the AN approach and NN approach. Density-based clustering is used instead of gating to satisfy the above first conditions. The determination of valid measurements based on density clustering was introduced in Ref. [8], which works based on the AN approach. However, the development of a new approach to the selection of validated measurements for updating the position of the targets is the main purpose of the present study, which satisfies the second condition. Two strategies are introduced for reaching this goal. Finally, the main contributions and significant features of the proposed DA technique can be summarized as follows:

- It does not require a gating technique for the determination of valid measurements.
- It does not require either knowledge of the false alarm or the detection probabilities.
- Important valid measurements are used and let efficiency in real-time and complex tracking systems.

The remaining of the paper is organized as follows. In section 2, the problem formulation is described. Section 3 discusses the proposed method, i.e., fuzzy density-based data association filter (FDB-DAF). The simulation results and performance comparisons are presented in Section 4 and the conclusions are provided in Section 5.

2- Problem Formulation

Suppose that there are T targets under surveillance, and the dynamics and measurement models of target $i \left\{ i = 1, 2, \ldots, T \right\}$, are as follows:

$$x_i(k) = F_i(k)x_i(k-1) + G_i(k)v_i(k) \tag{1}$$

$$z_i(k) = H_i(k)x_i(k) + w_i(k) \tag{2}$$

where $x_i\left(k\right)$ is an n-dimensional state vector, and $z_i\left(k\right)$ is an m-dimensional measurement vector of the i th target at time k. $F_i\left(k\right)$ is an $n \times n$ state transition matrix, $G_i\left(k\right)$ is an $n \times m$ noise matrix, and $H_i\left(k\right)$ is an $m \times n$

measurement transition matrix [21]. The process noise $v_i(k)$ and measurement noise $w_i(k)$ are independent zero mean Gaussian noise vectors with known covariance $Q_i(k)$ and $R_i(k)$, respectively.

$$Q_i(k) = Cov(v_i(k)) \tag{3}$$

$$R_i(k) = Cov(w_i(k)) \tag{4}$$

If the measurements do not contain any clutter or ECM (noise-free environment), the simple Kalman filter is used to predict and update tracks [9, 10].

$$\hat{x}_i(k+1|k) = F_j \hat{x}_i(k|k) \tag{5}$$

$$P_i(k+1|k) = F_i P_i(k|k) F_j^T + Q_i(k) \tag{6}$$

$$\hat{x}_i(k+1|k+1) = \hat{x}_i(k+1|k+1) + K_i(k+1)\tilde{z}_i(k+1) \tag{7}$$

$$P_i(k+1|k+1) = [\mathrm{I} - K_i(k+1)H_i(k+1)]P_i(k+1|k) \tag{8}$$

where $\tilde{z}_i(k)$ is the sum of all weighted innovations and $K_i(k)$ is denotes the gain of the Kalman filter that its formula is as follows :

$$\tilde{z}_i(k) = z_i(k+1) - H_i(k+1)\hat{x}_i(k+1|k) \tag{9}$$

$$K_i(k) = P_i(k|k-1) H_i(k)^T [H_i(k)P_i(k|k-1)H_i(k)^T + R_i(k)]^{-1} \tag{10}$$

The innovation covariance matrix is given by

$$S_i(k) = H_i(k)P_i(k|k-1)H_i(k)^T + R_i(k) \tag{11}$$

3- Fuzzy density-based data association filter

Suppose a measurement set $\{z_j, \mathrm{j}=1,\ldots,M_k\}$ is related to the target set $\{t_i, i=1,\ldots,T\}$ at time k. Measurements clustering, determining the membership degree of clustered (valid) measurements, and selection of important valid measurements are respectively the stages of the proposed DA approaches. The method requires the $MinPts$ and the Eps parameters for the clustering phase, which are the minimum number of points in the cluster and the maximum radius of the neighborhood, respectively. The proposed method starts with $\hat{x}_i(k+1|k)$ and take into account all $Eps\_neighborhood$ (measurements with the maximum Eps distance) of this point and considers them as cluster members (valid measurements of target i th). Then, the $Eps\_neighborhood$ of all cluster member measurements with least $MinPts$ points are taken into account and added to the cluster. Also, the $Eps\_neighborhood$ of new members with the least $MinPts$ points are taken into account and added to the cluster. The above process is repeated for all targets ($\hat{x}_i(k+1|k)$). Finally, the clustered measurements are considered as valid measurements and the number of created clusters will be the same as the number of targets.

In the second part of the proposed data association method, the fuzzy membership degrees of clustered measurements were determined for the current targets based on the principle of maximum entropy as follows:

$$u_{ji} = \frac{e^{-\alpha_{opt} d\left(z_j, \hat{x}_i(k+1|k)\right)}}{\sum_{\mathrm{t}=1}^{T} e^{-\alpha_{opt} d\left(z_j, \hat{x}_t(k+1|k)\right)}} \tag{12}$$

where $\mathrm{d}\left(\mathrm{z_j}, \hat{x}_i(k+1|k)\right)$ represents the Euclidean distance between the measurement z_j and the predicted position of the target $\hat{x}_i(k+1|k)$. Predicting the position of targets is considered as the cluster's center in the fuzzy membership degree determination process. α_{opt} is known as a discriminating factor, and its optimal is calculated as follows [14, 15, 27]:

$$\alpha_{opt} = -\frac{\ln \varepsilon}{d_{min}}, \varepsilon = 0.000001 \tag{13}$$

As mentioned above, this study suggested a new approach to the DA process, which is based on using important measurements for updating the position of the targets. Two strategies for the selection of important measurements can be applied. In the first strategy, k measurements with the highest degree of membership from valid measurements are selected. Selection of k measurements performed separately for each cluster (target) as follows:

$$\beta_i^j = \begin{cases} u_{ji} & \text{if } u_{ji} \text{ be owned by k} \\ & \text{measurements with the highest degree} \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

$$, j = 1, \ldots, N_k$$

where N_k is the number of valid (clustered) measurements and β_i^j indicates the distance between the measurement z_j and the ith target.

The second strategy, abandon measurements with very small u_{ji}. For reconstruction of the association probability matrix, a new rule is developed as follows:

$$\beta_i^j = \begin{cases} u_{ji} & \text{if } u_{ji} \geq \xi, \\ 0 & \text{otherwise} \end{cases} \quad ,j = 1, \dots, N_k \tag{15}$$

where ξ is the threshold value. Eventually, the probability matrix must be normalized as follows:

$$\beta = \begin{bmatrix} \beta_1^1/N_1 & \beta_1^2/N_1 & \dots & \beta_1^{N_k}/N_1 \\ \beta_2^1/N_2 & \beta_2^2/N_2 & \dots & \beta_2^{N_k}/N_2 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_T^1/N_T & \beta_T^2/N_T & \dots & \beta_T^{N_k}/N_T \end{bmatrix}, \tag{16}$$

$$N_t = \sum_i^{N_k} \beta_t^i \quad t = 1, \dots, T$$

Figure 3 illustrates the proposed algorithm for data association problems.

4- Simulation Results

This section presents two scenarios, 1) the linear crossing targets and 2) maneuvering targets to evaluate the proposed method compared to fuzzy nearest neighbor (FNN) [11], joint probabilistic data association filter(JPDAF)[10, 31, 32], maximum entropy fuzzy joint probabilistic data association filter(MEF-JPDAF) [22], and fuzzy genetic algorithm (Fuzzy-GA)[12]. Both scenarios were studied in two different levels of clutter that it is considered spatially distributed with Poisson distribution with parameter λ (the number of false measurements per unit of volume (km^2)). Root mean square error (RMSE) is used as evaluation criteria. It was calculated based on 100 runs of Monte Carlo simulation.

$$RMSE_k = \sqrt{\frac{1}{N_{MC}} \sum_{n=1}^{N_{MC}} \left(\hat{x}^n(k) - x_{true}^n(k)\right)^2 + (\hat{y}^n(k) - y_{true}^n(k))^2 + (\hat{z}^n(k) - z_{true}^n(k))^2} \tag{17}$$

where $(\hat{x}^n(k), \hat{y}^n(k), \hat{z}^n(k))$ and $(x_{true}^n(k), y_{true}^n(k), z_{true}^n(k))$ denote the estimated and true target positions at time k at the nth Monte Carlo (MC) simulation run, N_{MC} is the total number of independent MC runs.

The proposed DA technique has two parameters (MinPts and Eps) for measurement clustering that an investigation phase of trials and errors has been accomplished to set the right values of these parameters. Eventually, 3 and 0.55C were considered for MinPts and Eps, respectively. Also, C represents the volume of m-dimensional hypersphere validation gate units.

4- 1- Linear Crossing Targets

In this scenario, three crossing targets with initial state vectors $x_1(0) = [1\text{km} \; 0.25\text{km/s} \; 9.3\text{km} \; -0.1\text{km/s}]^T$, $x_2(0) = [1\text{km} \; 0.25\text{km/s} \; 4.3\text{km} \; 0.1\text{km/s}]^T$ and $x_3(0) = [1\text{km} \; 0.25\text{km/s} \; 11.3\text{km} \; -0.1\text{km/s}]^T$ are considered[5, 24]. The actual and estimated track of targets for this scenario is shown in Figure 2. The models of motion and measurement of targets are defined by (1) and (2). The measurement matric H and the state transition matrices F and G are defined as [2, 33]:

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

$$G = \begin{pmatrix} \delta/2 & 1 & 0 & 0 \\ 0 & 0 & \delta/2 & 1 \end{pmatrix}^T \tag{19}$$

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \tag{20}$$

where δ is the sampling interval. The covariance matrices $Q_{2\times2}$ and $R_{2\times2}$ are the system noise and measurement noise, which are assumed to be $Q_{ii} = (0.02^2)\, km^2$ and $R_{ii} = (0.0225)\, km^2$ $(R_{ij} = Q_{ij} = 0, \text{ for } i \neq j)$, respectively.

Table 1 clarifies the RMSE of the target position for FNN, JPDAF, and Fuzzy-GA. Comparing the RMSE of targets shows that the tracks of target 3 have the highest RMSE while the tracks of targets 1 and 2 have almost the same RMSE. Also, DNN and Fuzzy-GA, have respectively the highest and lowest RMSE in between compared techniques. Further, the value of RMSE increases by increasing the clutter level, which is less for Fuzzy-GA than the other methods. Table 2 shows the average RMSE for different k and ξ levels for the proposed approach. The results depict with increase k let to a decrease in RMSE values of targets. Against this, there is an increase in the RMSE values with an increase in threshold levels. For k=1, the proposed method solves the DA problem based on the NN approach, whereas its results are better than the FNN method. Moreover, the proposed DA approach based on the use of all valid measurements has the best results compared to other techniques. Finally, in comparison to the proposed strategies, the second strategy has better results. However, the selection of strategy and its level is dependent on application.

Input: $\hat{x}_i(k+1|k)$ and received measurements

Output: the measurements with the highest degree of membership

$D_{unprocessed}$ = receive measurements
$no\_of\_clusters = 0$
For i=1 to T **do**
    $no\_of\_clusters = no\_of\_clusters + 1$
    $Eps\_neighborhood\_set = Determine\ all\ Eps - neighborhood\ \ in\ D\ from\ \hat{x}_i(k+1|k)$
    For *each q from Eps_neighborhood_set* **do**
        $D_{unprocessed} = D_{unprocessed} - \{q\}$
        $\{q\}\ add\ to\ cluster_{no\_of\_clusters}$
        add all $Eps - neighborhood$ q to $Eps\_neighborhood\_set$
    End For
End For
For j=1 to $no\_of\_valid\ measurements$ **do**
    For i=1 to $no\_of\_clusters$ **do**
        membership u_{ij} is calculated via Equation (12)
    End For
End For
For i=1 to $no\_of\_clusters$ **do**
    reconstruct the association probability matrix via Equation (15) **Or** (16)
End For
/The remaining measurements in $D_{unprocessed}$ are invalid measurements/
$*/\ no\_of\_valid\ measurements = \sum_{k=1}^{no\_of\_clusters} |cluster_k|\ /*$

Fig. 1. Fuzzy density-based data association filter algorithm.

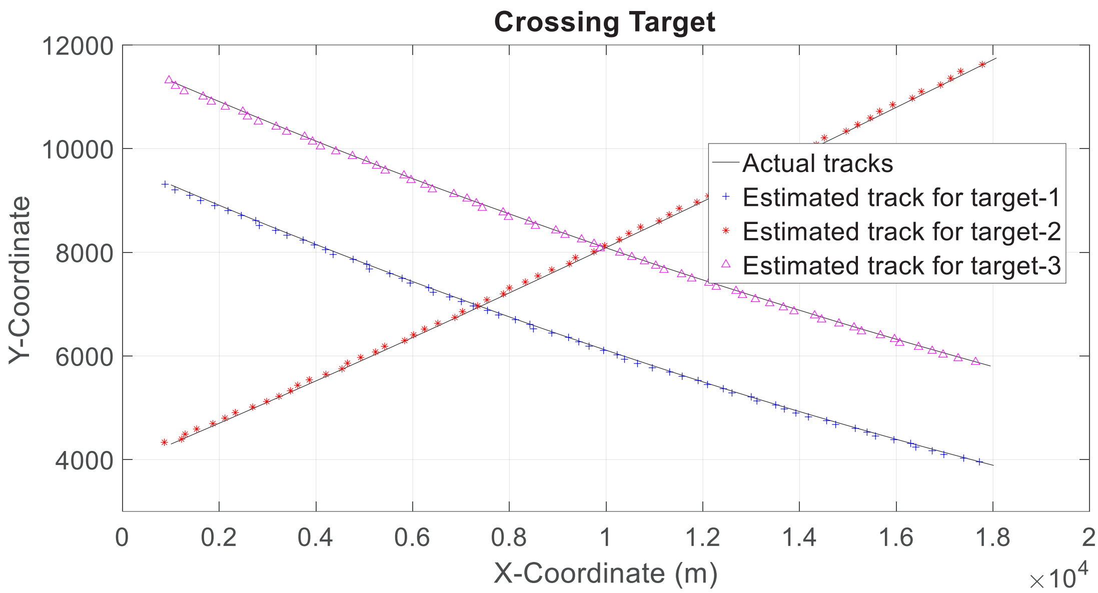

Fig. 2. Actual and estimated tracks by FDB-DAF in the first scenario.

Table 1. The RMSE position for compared methods in the first scenario.

Methods	Clutter density (λ)	Target-1	Target-2	Target-3
FNN	$\lambda = 1$	38.31	38.07	52.94
	$\lambda = 2$	41.20	37.89	54.14
JPDAF	$\lambda = 1$	26.43	25.68	37.41
	$\lambda = 2$	28.18	26.93	39.03
MEF-JPDAF	$\lambda = 1$	28.67	26.24	42.69
	$\lambda = 2$	30.15	27.86	45.94
Fuzzy-GA	$\lambda = 1$	17.81	17.28	30.73
	$\lambda = 2$	18.62	18.45	34.83

Table 2. The RMSE position for FDB-DAF in the first scenario.

Proposed approach		Target-1	Target-2	Target-3
First strategy	$k = 1$	34.72	33.19	43.07
	$k = 2$	32.28	31.11	40.48
	$k = 3$	29.60	28.22	38.55
	$k = 4$	25.59	24.42	37.24
	$k = 5$	21.86	20.84	35.41
Second strategy	$\xi = 0.10$	18.16	17.81	31.08
	$\xi = 0.25$	19.44	18.98	33.16
	$\xi = 0.50$	21.90	20.56	37.64
	$\xi = 1.00$	24.34	23.71	41.95
	$\xi = 1.50$	29.08	28.49	45.76
All measurements		17.32	17.14	31.52

Table 3. Simulation parameters in maneuvering crossing targets.

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

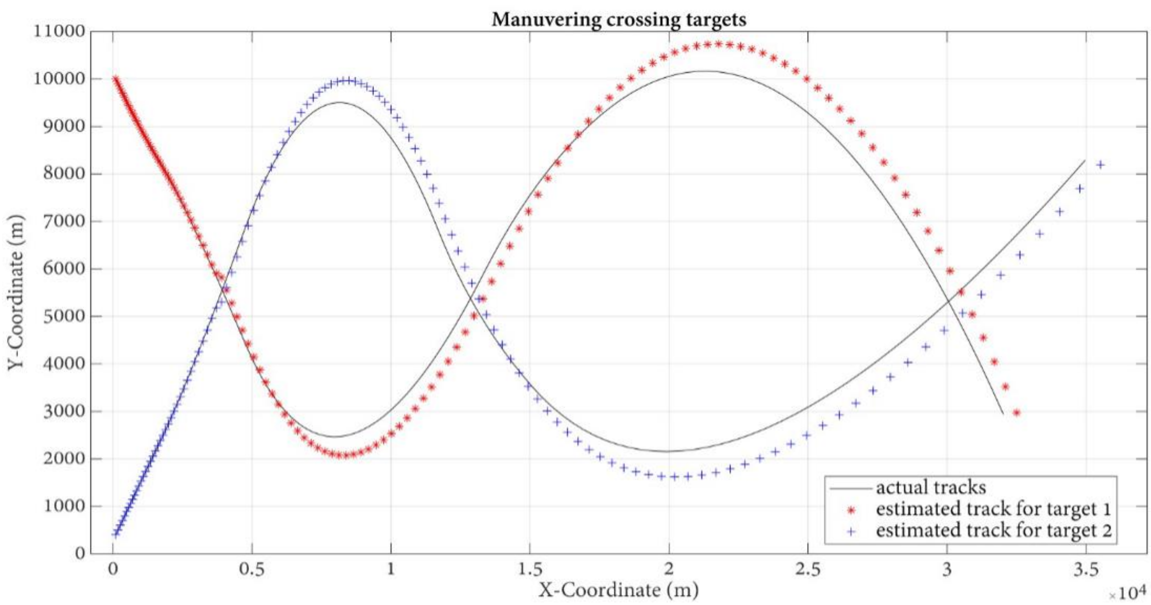

Fig. 3. Actual and estimated tracks by FDB-DAF in the second scenario.

4- 2- Maneuvering targets

For a deeper analysis of FD-JPDAF performance, a scenario of maneuvering crossing targets is considered. The acceleration is considered by additive term in the maneuvering model, which is given by[2, 34] as follows:

$$x_i(k+1) = F_i(k)x_i(k) + C_i(k)u_i(k) + G_i(k)v_i(k) \tag{21}$$

where $u_i(k) = [a_x(k)\ a_y(k)]^T$ is the acceleration input vector. By adding the acceleration term to the state equation, FDB-DAF was changed based on the MIE [31] by considering the acceleration term in the state equation. The state transition matrices F and G, and the measurement matrix H are similar to the previous example ((19) to (21)), and the new matrix C in (19) is the same as G. The covariance matrices $Q_{2\times2}$ and $R_{2\times2}$ are the system noise and measurement noise, which are assumed to be $Q_{ii} = 1$ and $R_{ii} = (60^2)m^2$ $(R_{ij} = Q_{ij} = 0,\ for\ i \neq j)$, respectively. Table 3 shows the acceleration vector parameters and initial state vector for this scenario. Figure 3 presents the actual target tracks and tracks estimated by FDB-DAF.

Table 4. The RMSE position for compared methods in the second scenario.

Methods	Clutter density (λ)	Target-1	Target-2
FNN	$\lambda = 1$	581.68	577.40
	$\lambda = 2$	635.02	629.75
JPDAF	$\lambda = 1$	361.67	355.83
	$\lambda = 2$	390.46	385.92
MEF-JPDAF	$\lambda = 1$	348.91	342.05
	$\lambda = 2$	376.28	368.11
Fuzzy-GA	$\lambda = 1$	312.72	308.45
	$\lambda = 2$	338.59	332.96

The RMSE of targets' positions for compared techniques are demonstrated in Table 4. By comparing results, it is evident that Fuzzy-GA average position RMSE is improved compared to other techniques. Multiple simulations with different clutter densities are considered to evaluate the performance of compared methods. The model parameters, process noise, and measurement noise are assumed fixed. As seen in Table 4, increasing clutter density caused a decrease in the algorithm's performance.

Table 5 shows the average RMSE for different $\boldsymbol{k}$ and $\hat{\boldsymbol{\iota}}$ levels of the FDB-DAF. In this scenario, the proposed is evaluated with two different clutter densities. By comparing results, it is evident that FDB-DAF efficiency is comparable to the compared methods. Also, same previous scenario, the proposed technique performance is improved by increasing k and decreasing $\hat{\boldsymbol{\iota}}$ for the first and second strategies, respectively. Moreover, results show a decrease in the accuracy of FDB-DAF in the case of clutter increasing to 6%. However, the most effective increases in clutter density were found for FNN, JPDAF, and followed by MEF-JPDAF. However, FDB-DAF with all measurements and Fuzzy-GA, has a similar effect due to clutter density increasing.

4- 3- Computational complexity

The execution time of the developed DA approach (based on all measurements) and other compared techniques for two scenarios are illustrated in Table 6. The programs were run on a computer with Intel(R) Core(TM) i7-6500 CPU 2.50 GHz, 8 GB RAM, and 100 Monte-Carlo runs. As seen in Table 6, FDB-DAF has the least execution time than the other algorithms. The reason is that FDB-DAF uses of density clustering approach to obtain valid measurements and does not require a gating technique. The clustering phase has a time order proportional to $O\left(T \times M_k\right)$. It can be observed that 1) determining the membership degreases of valid measurements and 2) determining the membership degree of abandoned measurements with very small fuzzy membership degrees have a time order of to $O\left(T\right)$ and $O\left(N_k \times T^2\right)$, respectively. The time order of the developed DA technique is equal to $O\left(N_k \times T^2\right)$. However, Fuzzy-GA has the most execution time due to the need to cross over, mutations, and selection for each chromosome.

5- Conclusion

In this paper, a robust fuzzy density clustering technique for solving DA problems in multiple tracking systems has been developed. It has employed jointly the density-based clustering and maximum entropy approach for valid measurement determination and their fuzzy membership degree. At the same time, two strategies have been introduced for the selection of important measurements. The advantage of the proposed technique is that it does not need gating to eliminate invalid measurements. Also, the execution time of the proposed method has been better in comparison with the other techniques. Furthermore, the clustering phase of the proposed approach has been able to be integrated with other DA approaches as a valid measurement detection process. Moreover, the efficiency and effectiveness of the developed technique have been considered based on simulation data. Using tree-based structures to expedite the computational cost of the proposed method has been under study as future research.

Table 5. The RMSE position for the proposed approach in the second scenario.

Proposed approach		$\lambda = 1$		$\lambda = 2$	
		Target-1	**Target-2**	**Target-1**	**Target-2**
First strategy	$k = 1$	529.47	517.63	578.60	515.53
	$k = 2$	482.11	469.81	521.37	507.46
	$k = 3$	413.05	396.90	446.82	425.74
	$k = 4$	338.27	324.07	364.41	350.38
	$k = 5$	326.70	313.73	348.72	336.06
Second Strategy	$\xi = 0.1$	311.96	308.07	332.50	330.98
	$\xi = 0.25$	324.83	320.41	347.28	342.66
	$\xi = 0.5$	389.54	375.77	415.18	401.34
	$\xi = 1$	427.06	410.25	459.46	443.92
	$\xi = 1.5$	473.94	461.47	510.85	499.04
All measurements		296.43	274.99	317.02	296.37

Table 6. Comparison of execution time in seconds.

Methods	Linear Crossing Targets	Maneuvering Targets
FNN	0.34	7.82
JPDAF	1.41	27.91
MEF-JPDAF	0.82	25.59
Fuzzy-GA	4.79	113.84
FDB-DAF	0.63	12.42

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