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A New Method for Multipath Clustering for Over-the-Horizon Radar

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Abstract: Over-the-Horizon Radar (OTHR) exploits the refraction of high frequency radiation through the ionosphere layers to detect targets beyond the line-of-sight horizon. Multipath propagation between the radar and the detected targets may results in multiple spatially separated tracks for a single target to be observed at the receiver site. Consequently there is a heavy traffic, especially in case of multiple targets, to be associated and combined if there are tracks represent the same target. In this study, a new method for multipath clustering for OTHR is proposed. The proposed method describes the similarities between all tracks as fuzzy degrees of membership. This method can operate in real-time and can perform clustering and fusion of OTHR tracks with tracks from other sources such as targets reporting global positioning systems and microwave radars. The proposed method has the advantages of less computations and high efficiency compared to conventional fuzzy logic clustering techniques. It has also the advantage of treating all the tracks data at once rather than pairwise. The efficiency of the proposed method is demonstrated using simulated examples.

Keywords: Over-The-Horizon Radar, Track Correlation, Track Association, Track Fusion

Introduction

Multisensor data fusion systems have many civilian and military applications (Aziz, 2014a; 2014b). Some of these applications are diversity communication systems (El-Ansary *et al.*, 2013; Aziz, 2011a), target detection (Aziz, 2010; El-Ayadi *et al.*, 1996), distributed radar surveillance networks (Aziz, 2014c; Aziz, 2008), wireless sensor networks (Aziz *et al.*, 2011; Aziz, 2011b), biomedical applications (El-Badawy *et al.*, 2014; 2013) and target tracking (Aziz, 2013; 2011c). An association technique is essential processing in multisensor data fusion systems (Hall, 1992). We focus on association in case of surveillance systems (Bogner *et al.*, 1998; Rutten *et al.*, 2004; Aziz *et al.*, 1999).

Wide area surveillance can be achieved using a high frequency (3-30 MHz) skywave Over-the-Horizon Radar (OTHR) which uses the ionosphere layers in the sky as a reflection medium. The ionosphere refracts the high frequency signals incident upon it. Refracted signals from one target that return to earth cause multiple appearances of the same target track to be observed (Singh and Bailey, 1997; Zhu *et al.*, 1994). For example,

with three ionosphere layers, one target can produce up to six tracks. These tracks are due to the six possible reflection paths. This problem, which is called Multiple Tracks Common Source (MTCS) problem, causes serious problems in target detection, identification and tracking. An association approach is essentially needed to merge the MTCS tracks into unique set of tracks that represent the true number of targets.

In OTHR, all the measured tracks are processed to decide whether two or more tracks represent the same target or not. Track association correlates redundant tracks, which are provided from multiple reflection paths on the same targets, into a unique set of tracks that represents the actual number of targets. Track fusion combines two or more tracks when it is decided that they represent the same target. Fusing data can enhance the quality of information to the end user of an OTHR (Sengupta and Iltis, 1989; Root, 2003). Track fusion is a part of level 1 processing (fused position and identity) in a data fusion model which incorporates level 2 processing (situation assessment) and level 3 processing (threat assessment) (Aziz, 2007).

There are many approaches in the literatures to perform track association and track fusion (Hall, 1992; Aziz *et al.*, 1999). The first track association technique was developed by (Singer and Kanyuck, 1970). Their correlation technique simply represents a gating technique. Two track estimates, from two different systems, are said to be correlated if and only if the difference between all their features fall within certain gates. The gate sizes depend on the system accuracy in terms of the feature noise standard deviations. Singer and Behnke (1970) considered the same problem and developed a track association technique based on a test statistic assuming that the estimation errors of different systems are independent. The common test statistic is a weighted estimates difference that depends on the covariance associated with each estimate. The classical technique for track association and fusion for OTHR requires hypothesizing the states of the ionosphere conditions, including the number of ionosphere layers and the height for each layer and testing each hypothesized track against observed tracks (Bogner *et al.*, 1998; Rutten *et al.*, 2004). This solution is computationally expensive. Furthermore, it assumes stationarity of the ionosphere layers which might not be realistic, since the ionosphere layers tend to change rapidly due to many phenomena related to wind, season and sun. The neural networks are also used to solve this problem (Zhu *et al.*, 1994; Sengupta and Iltis, 1989). The major drawbacks to the neural network implementations are that they require unreasonable numbers of neurons and require training with a very large set of tracks. Furthermore, they require training of such approaches with a very large set of tracks representing the OTHR tracking system.

Fuzzy techniques are also used to solve the problems of track association and track fusion (Root, 2003; Aziz, 2009a; 2009b). Using fuzzy techniques, the features are fuzzified using membership functions. The outputs from the fuzzification are soft values between zero and one and represent the correlation between all the tracks. These outputs are called fuzzy outputs. The fuzzy outputs from the fuzzification process are processed using fuzzy rules represented as IF THEN rules. The defuzzification process converts the fuzzy outputs to non-fuzzy outputs, which are called crisp data. The defuzzification outputs are analyzed and compared with each other or with thresholds to determine whether two/more tracks, obtained from two or more different sensors, represent the same target. Unfortunately, the extension of fuzzy track association to the case of a large number of tracks/targets is fairly complex due to the required large number of IF THEN rules (Aziz, 2014c; Aziz *et al.*,

1999). 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 addition, the solution of the conventional fuzzy logic approach to the track association problem is an approximate solution and the accuracy depends on several factors including the number of input variables, the number of linguistic variables, the choice of membership function and the accuracy of the fuzzy rules and statements. In general, the computational cost in generating the optimal solutions to the problems of track association and track fusion is usually excessive and infeasible for real-time surveillance systems. Furthermore, they assume idealized modeling assumptions and a prior knowledge of the signal environment, which is limited in practice.

This paper proposes a new method for multipath clustering for OTHR. The proposed method solves the problem of MTCS and also able to fuse target tracks to enhance the quality of target estimate. It reduces the number of target tracks and associate duplicate tracks by determining a similarity matrix of degrees of membership for all tracks. It generates a fuzzy likelihood measure instead of the Euclidean distance. The degrees of memberships are then compared to decide whether the tracks represent the same target or not. The proposed method is able to perform track association 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. Problem formulation and track clustering are briefly mentioned in section 2. The proposed multipath clustering for OTHR are presented in section 3. Performance evaluation and numerical results based on Monte Carlo simulations are reported in section 4. Performance comparisons with other multipath clustering techniques are also presented in section 4. Finally, section 5 contains a summary.

Problem Formulation

We assume that there is a multipath propagation due to three ionosphere layers. In this scenario, we assume two OTHRs observe four targets. Due to the three ionosphere layers, the number of reported tracks will be 24 tracks (although we only have 4 targets). We assume that each track, T_{ij} , $i = 1, 2, 3, 4$ $j = 1, 2, \dots, 6$, has two features, which are the x and y positions of the observed targets. Each report, T_{ij} , represents a track j due to observing target i . The goal is to find out which tracks represent the same target and which tracks represent different targets. The second goal is to fuse the tracks together, when it is decided that they are similar. These problems can be solved using clustering techniques.

Measurements clustering determines a partition matrix U of elements μ_{ik} , which represents the degree of membership of a data point x_k in a fuzzy cluster i (with a cluster center v_i) (Singh and Bailey, 1997; Dubios and Prade, 1980). The degrees of membership are established by minimizing the sum of the squared errors weighted by the corresponding m^{th} power of the degree of membership. The results are:

$$\mu_{ik} = \frac{1}{\left[\sum_{j=1}^c \left(\frac{d_{jk}}{d_{ik}} \right)^{\frac{2}{m-1}} \right]} \forall i, k \quad (1)$$

$$v_i = \frac{\sum_{k=1}^n (\mu_{ik})^m x_k}{\sum_{k=1}^n (\mu_{ik})^m} \forall i \quad (2)$$

where, c is the number of clusters and n is the total number of measurements.

For given observations and prototype (initial) values, the optimum degrees of membership are given by Equation 2. Thus the optimum degrees of membership are determined from the following matrix (assume $n = c = 2$):

$$D = \begin{pmatrix} \|x_1 - v_1\|^2 & \|x_2 - v_1\|^2 \\ \|x_1 - v_2\|^2 & \|x_2 - v_2\|^2 \end{pmatrix} = \begin{pmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{pmatrix} \quad (3)$$

The degrees of membership describe the similarities between the elements of the matrix D . It is required to utilize fuzzy clustering to match our problem. Let T_i be the column vector of n_f features with corresponding accuracies A_i , $i = 1, 2, \dots, n_t$ where n_t is the total number of targets. The features (such as range, bearing and speed) have certain accuracies. It is required to decide whether the two tracks represent the same target or not. The idea of the proposed method is to convert all the feature's differences to one degree of membership. This degree of membership is compared with a threshold (another degree of membership). The threshold value represents the known physical limitations or specifications of the sensors. In case of OTHRs, it is based on bearing resolution, range resolution and speed error. Thus the threshold value for a given sensor is a single degree of membership that represents all its attribute resolutions. We consider this problem as a binary hypothesis-testing problem. The two hypotheses are:

$$H = \begin{cases} 1, & \text{the two tracks are the same} \\ 0, & \text{the two tracks are different} \end{cases} \quad (4)$$

Proposed Multipath Clustering for OTHR

We assume that due to ionosphere layers environment, there is n_t number of tracks, T_i , $i = 1, 2, \dots, n_t$, reported from n_o number of OTHRs. Each track has n_f number of features, i.e.:

$$T_i = \begin{pmatrix} \text{feature 1} \\ \text{feature 2} \\ \dots \\ \text{feature } n_f \end{pmatrix}, i = 1, 2, 3, \dots, n_t \quad (5)$$

with corresponding accuracies:

$$A_i = \begin{pmatrix} \text{accuracy of feature 1} \\ \text{accuracy of feature 2} \\ \dots \\ \text{accuracy of feature } n_f \end{pmatrix}, i = 1, 2, 3, \dots, n_t \quad (6)$$

The features may be range, bearing and speed with corresponding accuracies. Our goal is to find out which tracks are similar (represent the same target) and dissimilar (represent different targets) to each other and to fuse two or more tracks together, when it is decided that they are similar.

The distance between two tracks, p and q , is defined in terms of the norm of the difference vector as:

$$\delta_{pq} = [T_p - T_q]^T C_{pq}^{-1} [T_p - T_q] \quad (7)$$

where, C_{pq}^{-1} is the covariance matrix of the uncertainties of the least accurate track. The idea of the proposed method is to convert all the feature's differences to one soft value. This soft value is compared with a threshold (another soft value). The threshold value represents the known physical limitations or specifications of the sensors. In case of OTHRs, it is based on bearing resolution, range resolution and speed error. Thus the threshold value is a single soft value that represents all feature accuracies. By this way we define:

$$\delta_{pq} = \begin{cases} [T_p - T_q]^T C_{pq}^{-1} [T_p - T_q], & p \neq q \\ A_p A_p, & p = q \end{cases} \quad (8)$$

For n_t reported tracks, all the comparison terms can be defined in a matrix A as:

$$A = \begin{pmatrix} A_1' A_1 & [T_1 - T_2]' C_{21}^{-1} [T_1 - T_2] & \dots & [T_1 - T_{n_t}]' C_{1n_t}^{-1} [T_1 - T_{n_t}] \\ [T_2 - T_1]' C_{21}^{-1} [T_2 - T_1] & A_2' A_2 & \dots & [T_1 - T_{n_t}]' C_{2n_t}^{-1} [T_2 - T_{n_t}] \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ [T_{n_t} - T_1]' C_{n_t 1}^{-1} [T_{n_t} - T_1] & [T_{n_t} - T_2]' C_{n_t 2}^{-1} [T_{n_t} - T_2] & \dots & A_{n_t}' A_{n_t} \end{pmatrix} \quad (9)$$

i.e.:

$$A = \begin{pmatrix} \delta_{11} & \delta_{12} & \dots & \delta_{1n_t} \\ \delta_{21} & \delta_{22} & \dots & \delta_{2n_t} \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ \delta_{n_t 1} & \delta_{n_t 2} & \dots & \delta_{n_t n_t} \end{pmatrix} \quad (10)$$

Define Φ as a similarity matrix of elements $\varphi_{ij}, \forall i \& j$ which represents the similarity measure between tracks i and j , such that:

$$\varphi_{ij} \in [0,1], 1 \leq i, j \leq n_t, \sum_{i=1}^{n_t} \varphi_{ij} = 1 \quad \forall j, \quad (11)$$

$$0 \leq \sum_{j=1}^{n_t} \varphi_{ij} \leq n_t \quad i = 1, 2, \dots, n_t$$

Given an integer N define D_N as the sum of distance measures weighted by the N^{th} power of the corresponding similarity, i.e.:

$$D_N = \sum_{j=1}^{n_t} \sum_{i=1}^{n_t} (\varphi_{ij})^N \delta_{ij} \quad \forall i \& j \quad (12)$$

For a given N and $\{\delta_{ij} \forall i, j\}$, it is required to obtain the similarity measures $\{\varphi_{ij}, \forall i, j\}$. This is a clustering problem and can be solved using clustering techniques (Aziz, 2011c; Dubios and Prade, 1980; Bezdek, 1986). The solution for $\{\varphi_{ij}, \forall i, j \neq 0\}$ is given by:

$$\varphi_{ij} = \frac{(1/\delta_{ij})^{1/(N-1)}}{\sum_{l=1}^{n_t} (1/\delta_{il})^{1/(N-1)}}, \quad \forall i \& j \quad (13)$$

Thus we obtain the following similarity matrix:

$$\varphi = \begin{pmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} & \dots & \varphi_{1n_t} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} & \dots & \varphi_{2n_t} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \varphi_{n_t 1} & \varphi_{n_t 2} & \varphi_{n_t 3} & \dots & \varphi_{n_t n_t} \end{pmatrix} \quad (14)$$

where, φ_{ii} represents the degree of membership of the accuracy of track i and φ_{ij} represents the degree of membership of the difference between two tracks T_i and T_j with respect to track j (the degree of similarity between a pairs of tracks). The association (correlation) between two tracks p and q (track p is assumed to be more accurate than track q , i.e., $A_p(j) < A_q(j) \forall j$) can be determined based on the most accurate track (T_p) or on the least accurate track (T_q), i.e.:

$$CORR(p, q) = \begin{cases} 1, & \text{if } \varphi_{pq} \geq \varphi_{pp} \\ 0, & \text{if } \varphi_{pq} < \varphi_{pp} \end{cases} \quad (15)$$

$$CORR(p, q) = \begin{cases} 1, & \text{if } \varphi_{pq} \geq \varphi_{pp} \\ 0, & \text{if } \varphi_{pq} < \varphi_{qq} \end{cases} \quad (16)$$

With the diversity in the relative tracks accuracies, the global correlation of the central processor is always based on the least accurate track (Aziz, 2011c; Aziz *et al.*, 1999). In this case, the correlation between any two tracks p and q (q is less accurate) is defined as:

$$CORR(p, q) = \begin{cases} 1 & \text{if } \varphi_{pq} \geq \varphi_{qq} \Rightarrow \text{same tracks} \\ 0 & \text{if } \varphi_{pq} < \varphi_{qq} \Rightarrow \text{different tracks} \end{cases} \quad (17)$$

where, in general, $CORR(p, q)$ is the association decision based on the least accurate track ($\min(\varphi_{pp}, \varphi_{qq})$).

When it is decided that two or more tracks are aligned, i.e., they represent the same target, the next step is to fuse them into a unique global track. One approach to obtain the global track is to adopt the superior of the tracks (T_{sup} : Best accurate track). The second approach is to combine the tracks (T_c : Combined tracks) according to some weights. Aziz (2007) it is shown that under certain conditions the performance of the fused track may perform worse than the performance of the superior track. In this case, it is recommended to adopt the superior track and track fusion is not recommended. The superior track can be chosen according to tracks accuracies. If the tracks have the same accuracies, the superior track is chosen according to the operating performance and the relative distance to the target (Aziz *et al.*, 1999). The smaller the distance to the target the more accurate is the

track. In our approach, the superior track is determined automatically from the data. The superior track, T_{sup} , is the track that has maximum degree of membership in the diagonal elements of the similarity matrix i.e., $\max_i \{\phi_{ii}\}$. By this way, the superior track is determined according to the OTHRs accuracies as well as the similarity between all the estimated tracks. The same tracks can also be fused as a weighted sum of the tracks estimates. The weights are the corresponding degrees of membership. The fused estimate can be defined as a fuzzy average to yield an overall association score for the tracks which represent the same target, i.e., (assume s tracks are the same):

$$T_c = \left(\sum_{k=1}^s T_k \phi_{kk} \right) / \left(\sum_{k=1}^s \phi_{kk} \right) \quad (18)$$

The value N in (8) is called the exponential weight. Its value reduces the influence of small degrees of membership (measurements further away from target) compared to that of large degrees of membership (measurements close to targets). The larger $N > 1$, the stronger is this influence. The exponential weight N also influences the values of the degrees of membership. The larger the exponential weight, the fuzzier becomes the degrees of membership (the values of the elements of the similarity matrix Φ). No any theoretical justifications for choosing N exist (Dubios and Prade, 1980; Bezdek, 1986). We choose $N = 2$.

The proposed clustering approach has the following advantages: (1) Unlike most of previous OTHR clustering techniques, the proposed method can easily be applied to multi OTHRs as well as a single OTHR, (2) The membership functions are generated automatically from the data using fuzzy clustering, i.e., they are not chosen heuristically, (3) The degrees of membership of the tracks accuracies are affected 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 (adaptation to the environment), (4) The similarity between tracks is obtained by treating all the tracks at once rather than pairwise. (5) Since the proposed approach assigns only one degree of membership to each track rather than assigning one degree of membership for each feature, it reduces the computational complexity with a factor of n_f and the number of comparisons does not grow with the number of features. This also reduces the sensitivity of the final decision to individual features fluctuations and has the advantage of the soft decision over the hard decision, (6) The superior track is determined automatically from the tracks accuracies as well as the measurements, (7) Using the proposed clustering method, features containing kinematics and non-kinematics data can be clustered and

combined and (8) This method can perform clustering and fusion of OTHR tracks with tracks from other sources such as targets reporting global positioning systems and microwave radars.

Performance Evaluation and Comparison

To demonstrate the feasibility of the proposed approach to solve MTCS problem, it is applied to an example of two OTHRs detecting two targets in a two ionosphere layer environment. The two targets are tracked simultaneously by the two OTHRs. Due to multipath propagation, the number of tracks, reported to a central processor, by the two OTHRs is 16 tracks although there is only two targets. The center processor receives 16 tracks representing four reflections for each target. Each track consists of bearing (θ) and range (r) information of the observed target, i.e., (Aziz, 2014c; 2007):

$$T_i = \begin{pmatrix} \theta_i \\ r_i \end{pmatrix}, i = 1, 2, 3, \dots, 16 \quad (19)$$

The uncertainties of the two OTHRs are represented by the covariance matrix:

$$C_j = \begin{pmatrix} \sigma_{\theta_j}^2 & 0 \\ 0 & \sigma_{r_j}^2 \end{pmatrix}, j = 1, 2 \quad (20)$$

where, $\sigma_{\theta_j}^2$ and $\sigma_{r_j}^2$ represent the variances of the measurements error of bearing and range information, respectively. The reflections from ionosphere layers cause additional errors in bearing and range measurements. These errors are assumed to be normally distributed with zero means and variances $\sigma_{L_{\theta_j}}^2$ and $\sigma_{L_{r_j}}^2$ in bearing and range respectively, $k = 1, 2$ (two layers). The resolution of each OTHR is defined in terms of the measurement uncertainties as:

$$a_j = \begin{pmatrix} a_{\theta_j} \\ a_{r_j} \end{pmatrix} = \begin{pmatrix} 3\sigma_{\theta_j} \\ 3\sigma_{r_j} \end{pmatrix}, j = 1, 2. \quad (21)$$

The noise uncertainties of the OTHRs are assumed to be $\sigma_{\theta 1} = 0.5$ Radians, $\sigma_{r 1} = 20$ km, $\sigma_{\theta 2} = 0.55$ Radians and $\sigma_{r 2} = 30$ km. The layers variances are $\sigma_{L_{\theta 1}} = 0.6$ Radians, $\sigma_{L_{r 1}} = 50$ km, $\sigma_{L_{\theta 2}} = 0.65$ Radians and $\sigma_{L_{r 2}} = 55$ km. The actual targets trajectories are shown in Fig. 1. The tracks received from both OTHRs, due to multilayer environment, are shown in Fig. 2 and 3. Eight tracks are received from each OTHRs, thus there is sixteen tracks reported to the central processor as shown in Fig. 4. The central processor has to process all the

reported tracks and fuse the redundant tracks into a unique set of tracks. The fused tracks, after applying the proposed clustering technique, are shown in Fig. 5. Since the objective of any clustering approach is to determine

the right number of targets (2 targets in our example), it is clear from Fig. 5 that the proposed approach successfully associates all the reported tracks and yields satisfactory results.

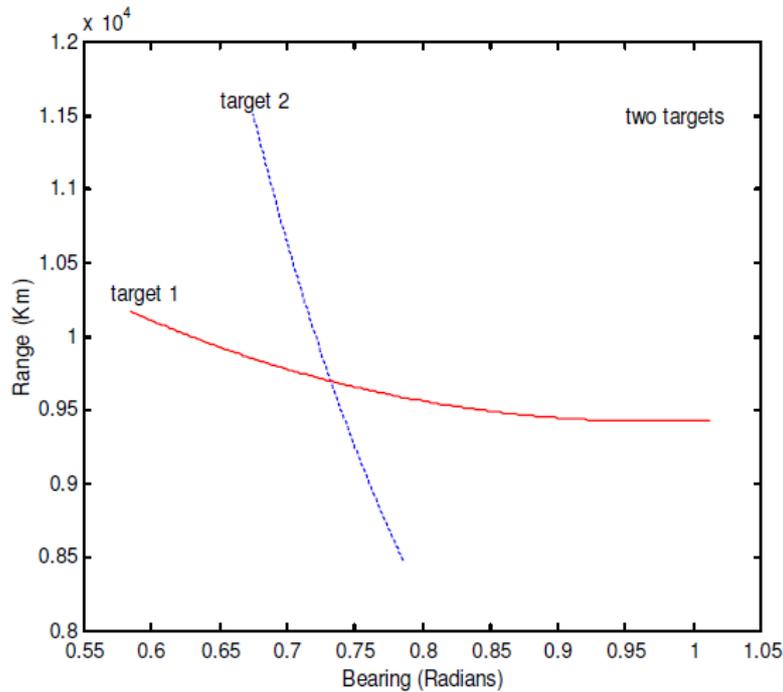


Fig. 1. Actual target tracks

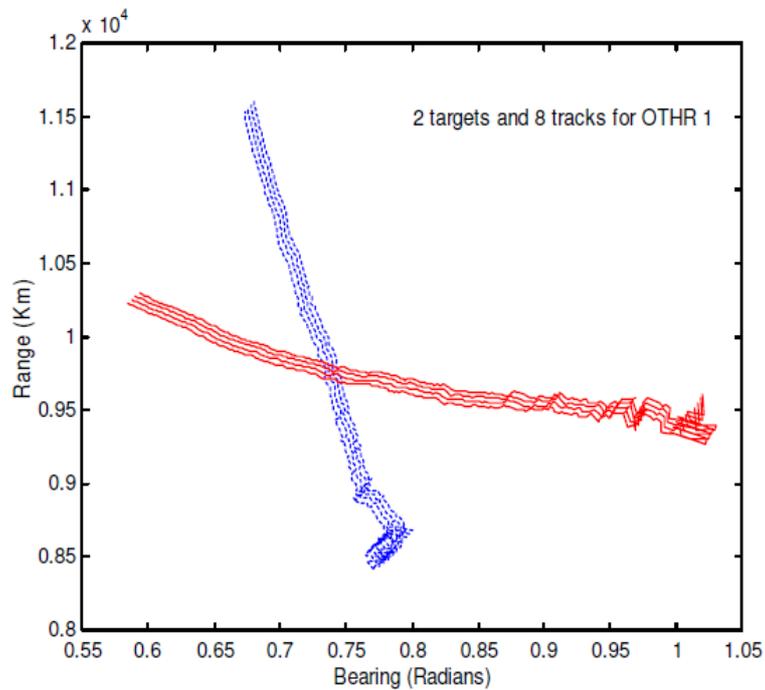


Fig. 2. Displayed tracks for OTHR 1 (before clustering)

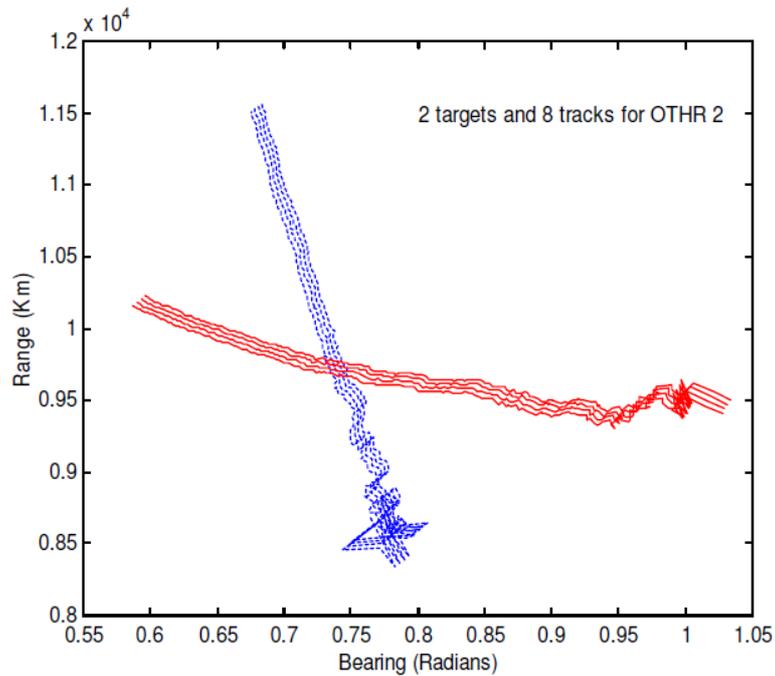


Fig. 3. Displayed tracks for OTHR 2 (before clustering)

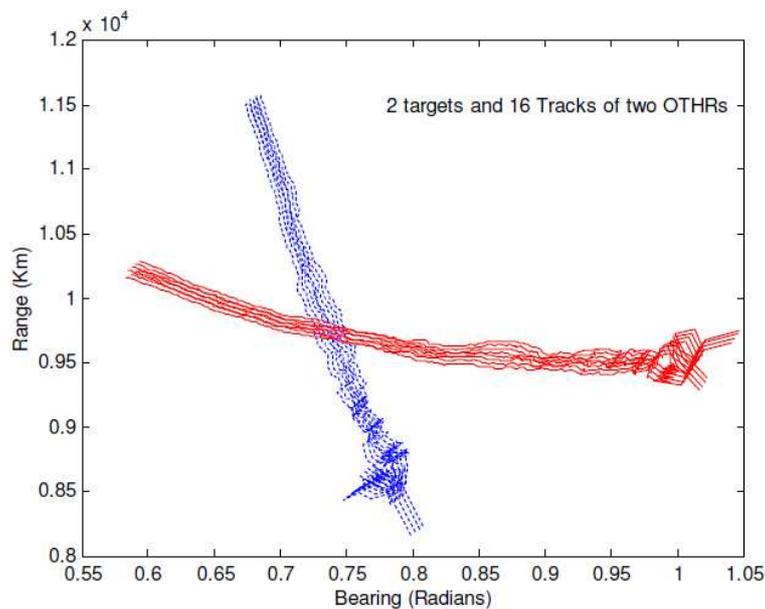


Fig. 4. Displayed tracks for two OTHR (before clustering)

The performance of the proposed method is compared with the performance of Euclidean clustering (Aziz, 2013; Hall, 1992) and conventional fuzzy logic clustering (using IF-THEN rules) (Singh and Bailey, 1997) in a simple example. We consider the case of a single target tracked by a single OTHR in a two ionosphere layers environment. Due to multipath propagation, the number of tracks, reported to a central

processor is 4 tracks (Fig. 6) although there is only one target. The central processor receives 4 tracks representing four reflections for the single target. The objective of any clustering approach is to determine the right number of clusters (one target in our case). For a given scan, a correct clustering occurs if the central processor decides that the four reflections represent a single target, otherwise an incorrect clustering occurs.

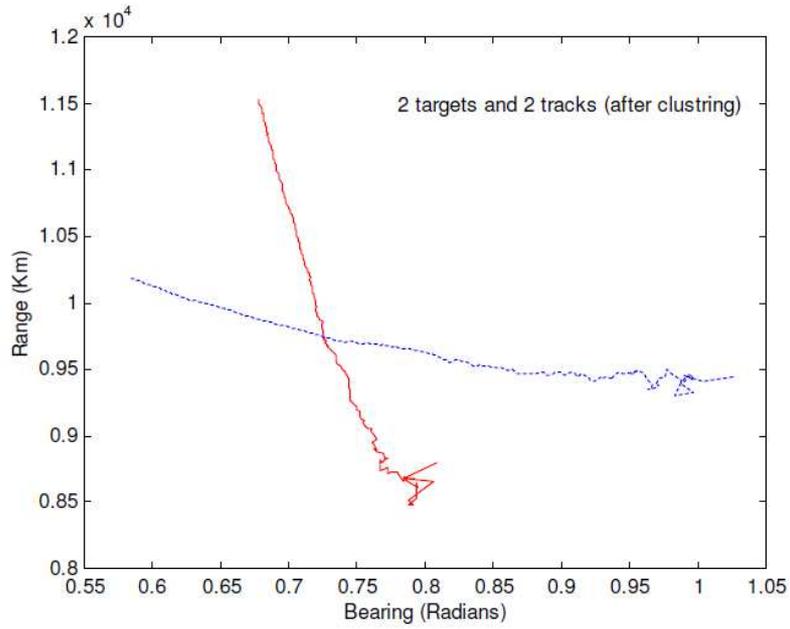


Fig. 5. Displayed tracks for two OTHR (after clustering)

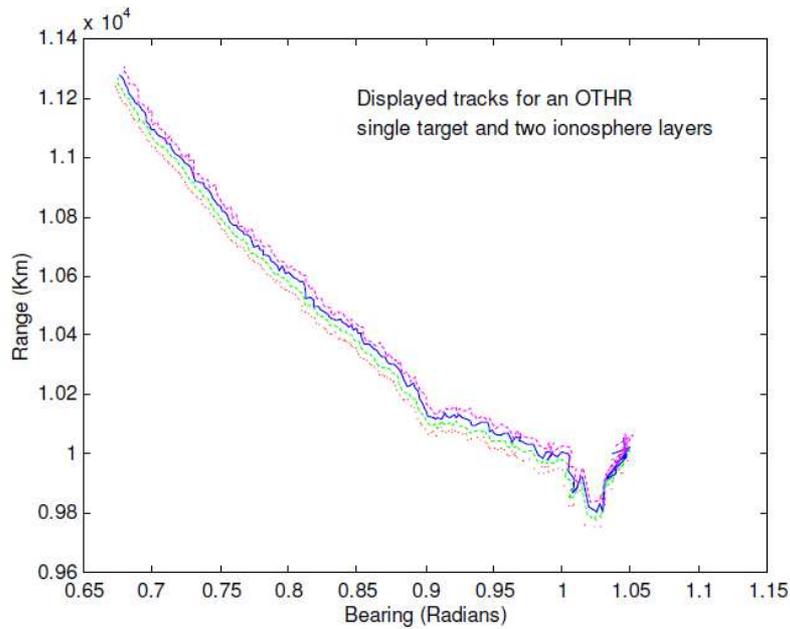


Fig. 6. Displayed tracks for an OTHR

Table 1. Comparison of percentage of correct clustering

Clustering method	Percentage of correct clustering (%)		
	$\sigma_\theta = 0.5$ Radians, $\sigma_r = 20$ km (%)	$\sigma_\theta = 1.0$ Radians, $\sigma_r = 50$ km (%)	$\sigma_\theta = 2.5$ Radians, $\sigma_r = 100$ km (%)
Euclidean	97	88	76
Euclidean fuzzy logic	99	93	81
Proposed method	100	97	90

Table 1 compares the percentage of correct clustering for different values of noise uncertainties. This percentage is obtained as an average value over 1000 runs. The percentage of correct clustering using Euclidean clustering varies from 76 to 97%, while it varies from 81 to 99% using conventional fuzzy logic clustering and varies from 90 to 100% using the proposed clustering approach. The performance of the proposed clustering approach is always better than the performance of the Euclidean and conventional fuzzy logic clustering for all values of uncertainties. The results show that the proposed clustering approach is much more efficient than the Euclidean clustering and the conventional fuzzy logic clustering.

We consider another example of moving maneuvering targets in a noisy environment. We assume an example of an OTHR detecting two targets in a two ionosphere layers environment (as the previous ionosphere environment and variances measurements). Due to multipath propagation, the number of tracks is 8 tracks although there is only two targets. The dominant acceleration in deterministic target maneuvers is coordinated turn. The reasons are: (1) Turns generate higher accelerations (up to ~ 9 g for an aircraft turn versus ~ 1 g for thrust), (2) targets prefer to maintain a high speed when in danger, turning rather than slowing down to avoid danger. Hence, turning motion models are the dominant models for target maneuver in tracking systems. The initial positions ((x, y) in meters)) of the three targets are assumed to be (6000, 8000) and (6100, 8100) for target 1 and 2, respectively. The target motion model has the form of

$$x(k+1) = Fx(k) + v(k) \quad (22)$$

and the corresponding measurement model is:

$$z(k) = H(k) x(k) + w(k) \quad (23)$$

where, $x(k)$ is an n dimensional state vector of a target at scan k , $z(k)$ is an m dimensional measurement vector (assuming $z(k)$ is the correct measurement for the target), $v(k)$ is a noise input vector, $w(k)$ is a measurement noise vector, F is an $n \times n$ state transition matrix and H is an $m \times n$ measurement matrix. The process noise and the measurement noise are assumed to be uncorrelated, zero mean Gaussian with covariance matrices:

$$Q(k) = Cov(v(k)) \quad (24)$$

$$R(k) = Cov(w(k)) \quad (25)$$

Each target track is predicted and updated based on correct measurements as follows (Aziz, 2014c; 2011c):

$$\hat{x}(k+1|k) = F\hat{x}(k|k) \quad (26)$$

$$P(k+1|k) = F P(k|k) F' + Q(k) \quad (27)$$

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + K(k+1)\tilde{z}(k+1) \quad (28)$$

$$P(k+1|k+1) = [I - K(k+1)H(k+1)]P(k+1|k) \quad (29)$$

where, the Kalman filter gain $K(k)$ and the innovation $\tilde{z}(k+1)$ are given by:

$$K_i(k+1) = P_i(k+1|k)H_i'(k+1) \times [H(k+1)P_i(k+1|k)H_i'(k+1) + R_i(k+1)]^{-1} \quad (30)$$

$$\tilde{z}(k+1) = z(k+1) - H(k+1)\hat{x}(k+1|k) \quad (31)$$

The covariance matrix of the innovation is given by:

$$S(k+1) = H(k+1)P(k+1|k)H(k+1) + R(k+1) \quad (32)$$

If there is no validated measurement, then:

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) \quad (33)$$

$$P(k+1|k+1) = P(k+1|k) \quad (34)$$

The state transition matrix F is given by:

$$F = \begin{pmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad (35)$$

where, T is the sampling interval.

The state vector $x(k)$ contains the x - and y - target positions and velocities, i.e.:

$$x(k) = \begin{pmatrix} x(k) \\ v_x(k) \\ y(k) \\ v_y(k) \end{pmatrix} \quad (36)$$

The measurements are the x - and y - target positions, i.e., the measurement matrix H is given by:

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \quad (37)$$

The process noise $v(k)$ has a covariance Q given by (Aziz, 2014c; Aziz *et al.*, 1999; Aziz, 2007):

$$Q = q^2 \begin{pmatrix} T^3/3 & T^2/2 & 0 & 0 \\ T^2/2 & T & 0 & 0 \\ 0 & 0 & T^3/3 & T^2/2 \\ 0 & 0 & T^2/2 & T \end{pmatrix} \quad (38)$$

where, q^2 is a scalar given by:

$$q^2 = a^2 T \quad (39)$$

and a is the acceleration.

The initial state estimates and the corresponding initial covariance matrix are obtained by two points

differencing of the measurements with a corresponding covariance matrix as in (Aziz, 2013; Aziz, 2011c). Each target motion is initially in a straight line with constant velocity. The measurements are taken every 0.1 sec. After generating 250 measurements, the targets institute a 10 g right turn ($g = 9.8 \text{ m}^2/\text{sec}$) and hold the turn for 100 measurements and then return to straight lines motion for an additional 250 measurements. The values of the noise uncertainties are taken as $\sigma_x = \sigma_y = 140 \text{ m}$ for all targets. The performance is evaluated based on 100-run Monte Carlo simulations.

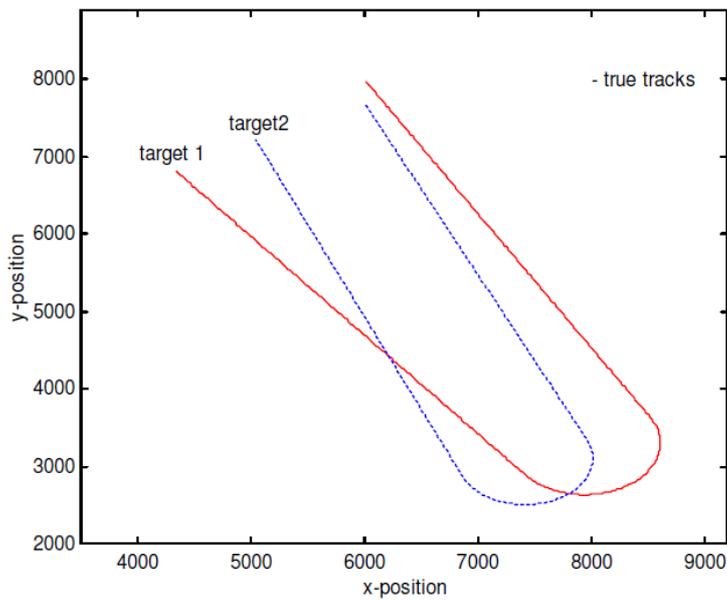


Fig. 7. True target tracks (two maneuvering targets)

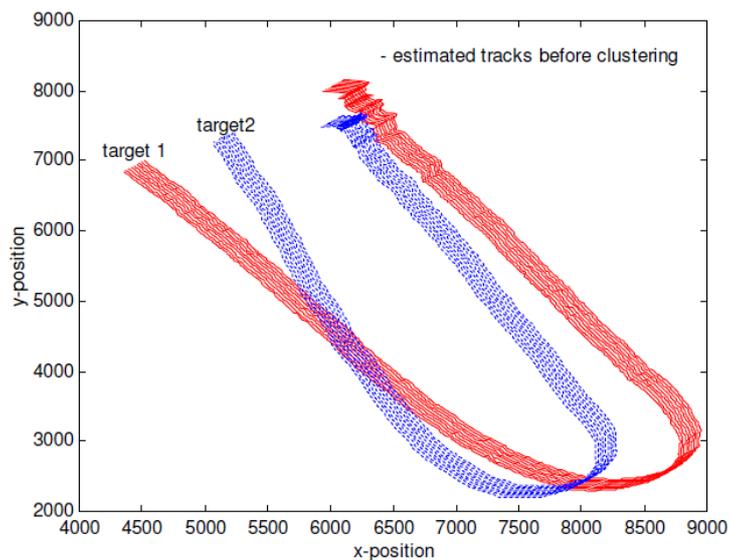


Fig. 8. Displayed tracks for OTHR (before clustering)

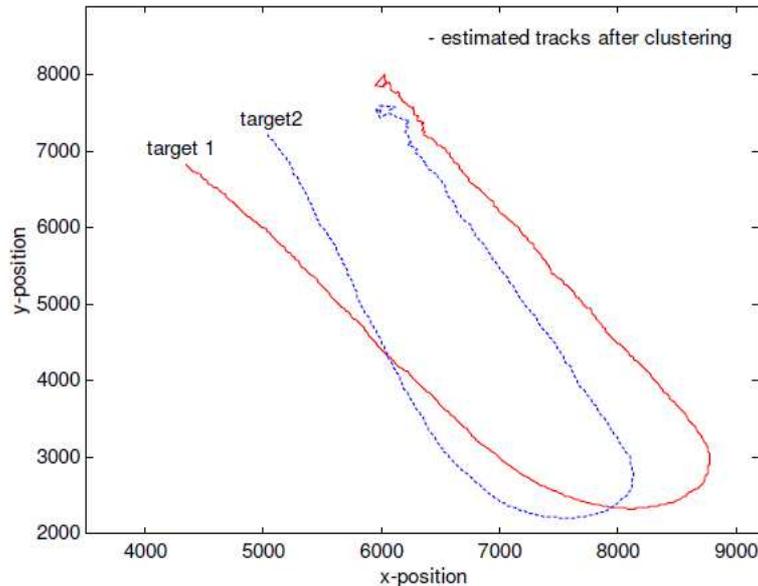


Fig. 9. Displayed tracks for OTHR (after clustering)

The actual targets trajectories are shown in Fig. 7. The tracks received from the OTHR, due to multilayer environment, are shown in Fig. 8. Eight tracks are received from the OTHR, thus there is eight tracks reported to the central processor as shown in Fig. 8. The central processor has to process all the reported tracks and fuse the redundant tracks into a unique set of tracks. The fused tracks, after applying the proposed clustering technique, are shown in Fig. 9. It is clear from Fig. 9 that the proposed approach successfully associates all the reported tracks and yields correct results.

Conclusion

The problem of MTCS due to multipath propagation has been considered. A new method for multipath clustering for OTHR is proposed. Similarity measures are obtained by taking into account all tracks accuracies and relative positions to targets. Unlike, conventional fuzzy clustering approaches in which the membership functions are chosen heuristically, the membership functions, using the proposed method, are generated automatically from the data. Performance evaluation of the proposed clustering method has been done and compared to Euclidean and conventional fuzzy logic clustering. It has been shown that the performance of the proposed method significantly outperforms the Euclidean and conventional fuzzy logic clustering. The proposed method also enables the fusion of OTHR tracks with other tracks from other sources. It has many advantages including reduction of the computational complexity, treating all the tracks data at once rather than pairwise and performance improvement.

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Author's Contributions

Ashraf M. Aziz: Developed the research idea and organized the study. Coordinated the overall framework and participated in all simulations, discussion, data-analysis as well as contributed to the writing of the manuscript.

Mohamed A. Abdel-Rahman: Organized the study. Coordinated the overall framework and participated in all simulations, discussion, data-analysis as well as contributed to the writing of the manuscript.

Saeed A. Al-Ghamdi: Organized the study. Coordinated the overall framework and participated in all simulations, discussion and data-analysis.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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