Fuzzy Binary Track Correlation Algorithms for Multisensor Information Fusion

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Abstract—A fuzzy binary track correlation algorithm and a fuzzy classical assignment algorithm are proposed for distributed multisensor data fusion in this paper. First, the corresponding composition of fuzzy element sets and selection of membership function are discussed. And then, dynamic assignment of weight vectors and multi-valency processing methods are designed. Finally, a fuzzy binary track correlation criterion is presented to improve accuracy. Moreover, the proposed algorithms are compared with two representational methods in classical simulations. The simulation results show that the performance of new algorithms is much better than that of traditional methods in complex scenarios. Specifically, the proposed algorithms improve the correlation accuracy in ~35% of the classical algorithms in the simulation.

Index Terms—Information Fusion; Track Correlation; Radar Network; Fuzzy Set

I. INTRODUCTION

Using measurements from multisensor system, the multitarget tracking technology has been largely applied to military affairs and public affairs. In some applications, the data is collected by many sensors distributed over a large area. In view of security, viability and communication bandwidth of such a multisensor system, it’s unreliable to process these data with centralized method. However, the distributed structure of processing method is appreciable. In this paper, we are specifically interested in track-to-track fusion and association problems [1~17] under distributed tracking situations, where each sensor has its own data processing capability to associate local data to form local tracks, and communicate (transmit) them, either to each other, or to a higher-level processing center, where local tracks are associated and fused into a set of global tracks.

Track-to-track association problem is a crux of distributed multisensor system. It’s a problem of how to decide whether two tracks coming from different sensor systems represent the same target. The issue of track-to-track association was first considered in [3] presented by Singer and Kanyuach, assuming tracks with independent estimation errors (Singer’s algorithm). Then, Bar-Shalom extended to the case of correlated errors in [4] (Bar-Shalom’s algorithm) and Kosaka presented the Nearest Neighbor (NN algorithm) in [5]. A K-Nearest Neighbor algorithm was given in [6] and Bowman proposed a Maximum likelihood algorithm in [7]. Chang and Youens transformed track-to-track association into Multidimensional assignment problem and get it resolved with Hunger/Munker method [8]. In these algorithms above, Singer’s algorithm, Bar-Shalom’s algorithm and NN algorithm are usually applied to the actual system. However, these algorithms will lead to false correlation or missing correlation when in the scenarios of dense targets, interfering, noise, track cross and so on.

To resolve these problems of Singer’s algorithm and Bar-Shalom’s algorithm, a fuzzy binary track correlation algorithm and a fuzzy classical assignment algorithm are presented based on the theory of fuzzy set and double threshold detection method. At the same time, the composition of fuzzy element set, the selection of membership function, the dynamic assignment of weight vector, the track mass designing and the multi-valency processing method are discussed in this paper. Some simulations for dense targets environments, more cross, split and maneuvering track situations are designed and the results show that correlative performance of these fuzzy binary track correlation algorithms are much better than that of the classical methods.

The rest of the paper is organized as follows: In the next section, Section II, we define a linear-Gaussian target model and a distributed sensor model, which will be used as the basis for the rest of this paper. In Section III, the novel fuzzy binary correlation algorithms are derived based on the theory of fuzzy set and double threshold detection method. This section also highlights important practical implementation issues of several important parameters like fuzzy element set and membership function in the proposed algorithms. The details of the simulations done and the comparisons of the performances of the proposed algorithm against several conventional algorithms are given in Section IV. The main contributions of this paper concluding remarks are summarized in Section V.

II. TRACK FUSION PROBLEM

According to [2], consider two sensors, \( i = 1, 2 \), which observe a common target as

\[
y_a = H_a x(t) + v_a
\]

(1)

at time \( t_k \), where \( k = 1, \ldots, N \), such that \( t_{k_1} < t_{k_2} < \cdots < t_{k_N} \), with observation matrices \( H_{a} \) of appropriate dimensions, each measurement error \( v_a \) is an independent zero-mean
Gaussian random vector, whose covariance matrix is $R_a$. The target state is modeled by a continuous-time vector stochastic process $(x(t) , t \in [t_0, \infty))$ defined by a linear stochastic differential equation

$$dx(t) = Ax(t)dt + Bdw(t)$$

with initial condition $x(t_0) = x_0$ at the initial time $t_0 = \min\{t_1, t_2\}$, given as a Gaussian vector $x_0$ with mean $\bar{x}_0$ and covariance matrix $\bar{Q}_0$, and a unit-intensity vector Wiener process $(w(t), t \in [t_0, \infty))$. We assume $x_0$, $w(t)$, and $((v_{ia})_{ia})_{ia}$ are all independent from each other. Without loss of generality, we assume each local sensor, $i = 1, 2$, processes each measurement, $y_{ia}$, $k = 1, \ldots, N$, by a Kalman filter to maintain target state estimates, and at a given fusion time $t_f \geq \max\{t_{N1}, t_{N2}\}$, communicates (transmits) the local state estimate $\hat{x}_i = E(x(t_f) | (y_{ia})_{ia} N)$, to each other, or a higher-order fusion center, together with its estimation error covariance matrix $Q_i$. (We use $E$ as the conditional and unconditional expectation operator, and $P$ and $p$ as the generic symbols for the conditional and unconditional probability density or mass function. By $X^T$ we will mean the transpose of a matrix or a vector $X$.)

Then our problem is to generate a fused target state estimate $\hat{x}_f$ by combining two local estimates $\hat{x}_1$ and $\hat{x}_2$.

For the sake of notational simplicity, let $x = x(t_f)$, $\bar{x} = E(x(t_f))$, $\bar{Q} = E((\bar{x} - x)(\bar{x} - x)^T)$ and $\hat{x}_i$, $\bar{x}_i$ be the local estimate and estimation error by sensor $i = 1, 2$, respectively. In order to evaluate various track fusion rules described in the next section, besides the local estimation error covariance matrices, $Q_i = E((\bar{x}_i - x)(\bar{x}_i - x)^T)$, which is obtain from the local Kalman filter, we may need the cross covariance matrices $Q_{ij} = E((\bar{x}_i - x)(\bar{x}_j - x)^T)$, reflecting the fact that (i) the local estimation errors, $\bar{x}_i$ and $\bar{x}_j$, are correlated with each other, through the common state initial condition $x_0$, as well as the common target dynamics process noise $w(t), t \in [t_0, t_f]$; (ii) and that each local estimation error $\bar{x}_i$ is not necessarily independent of the target state $x$.

III. FUZZY BINARY TRACK CORRELATION ALGORITHMS

As we all known, there are some fuzziness which can be indicated by the membership function of fuzzy mathematics in the track correlation. That’s to say, the similar degree of two tracks can be described by membership. Consequently, a fuzzy binary track correlation algorithm is proposed in this paper. In order to improve the validity of this algorithm, the element related to track correlation will be divided into two kinds: One kind is the element cannot be blurred, such as submarine, offing and airborne target type and so on; The other kind is the fuzzy element, such as the distance between location, speed and course of targets and so on. The non-fuzzy element can be differentiated by coarse correlation, which can reduce the complexity of fuzzy correlation.

A. Fuzzy Element Set

The fuzzy element set is supposed as $U = \{u_1, u_2, \ldots, u_k, \ldots, u_n\}$, where $k$ denotes the $k$-th fuzzy element related to correlation decision. Usually, the fuzzy element set may divide into three kinds: The first kind of fuzzy element set includes the difference between location, speed, course, and the acceleration of targets on X-axis. The second kind of fuzzy element set includes the difference between location, speed, course, and the acceleration of targets on X-axis, Y-axis, and Z-axis. The main difference among these three kind of fuzzy elements set maybe: The first kind set uses one-dimensional information of the target location, speed and acceleration; the second kind set uses two-dimensional information of the target location, speed and acceleration; and the third kind set uses three-dimensional information of the target location, speed and acceleration. Since the impacts of these fuzzy elements on the correlation decision are different, only the vital element is selected in practical application. In this way, it can guarantee the tracking ability to each kind of maneuvering target and does not make the algorithm excessively complex or increase the computational burden of system. From direct-viewing, the difference between location of targets on X-axis, Y-axis and Z-axis should be most important. And the next is the difference between speed of targets on X-axis, Y-axis and Z-axis. The third is the difference between courses of targets. These elements constitute the main body of fuzzy correlation decision, while the distance between acceleration and course of targets may take the assistance criterion, its weight value may be very small or zero. The weight corresponds to the fuzzy element set on $U$ is a fuzzy set: $\pi = (a_1, a_2, \ldots, a_k, \ldots, a_n)$, where $a_k$ is the weight corresponds to the $k$-th element ($u_k$) and $\sum_{i=1}^{n} a_k = 1$. The value of $a_k$ is given according to the importance of the $k$-th element’s impact on the correlation decision. According to the characteristic of the existed sensor, one can set $a_1 \geq a_2 \geq a_3 \ldots \geq a_n$. Due to the multiplicity of maneuvering target, the setting of $a_k$ should be variable.

B. Memberships Function

Membership function is the key of applying fuzzy set theory to resolve the track correlation problem. According to the characteristic of fuzzy element in track correlation, three kinds of membership function as follows are adopted:

Normally model:
\[ \mu(u) = \exp(-\tau_k (u^2 / \sigma_k^2)) \]  
(Cauchy model)

\[ \mu(u) = 1/(1 + \tau_k (u^2 / \sigma_k^2)) \]  
(Mediacy model)

\[
\begin{align*}
\mu(u) &= \begin{cases} 
1 & 0 \leq u \leq \tau_k \sigma_k \\
0 & |u| > 3\sigma_k 
\end{cases} 
\end{align*}
\]  
(5)

where \( \sigma_k \) is the extensibility degree of the \( k \)-th element in fuzzy element set on \( U \), and \( \tau_k \) is an indeterminate coefficient can be confirmed by simulation.

C. Fuzzy Correlation Criterions

1) Choice of Fuzzy Element and Initial Value of Weight Vector

To gain the member ship of each fuzzy element, the fuzzy element set \( u_k (k=1,\ldots,n) \) between tracks should be established based on state estimation \( \hat{X}_i (l) \) and \( \hat{X}_j (l) \).

Let \( \hat{X}(l) = (\hat{X}_i (l), \hat{Y}_i (l), \hat{X}_j (l), \hat{Y}_j (l), \hat{X}_i (l), \hat{Y}_i (l), \hat{X}_j (l), \hat{Y}_j (l), \hat{X}_l (l), \hat{Y}_l (l))^n \) be the state estimation, the fuzzy element and initial value of weight vector can be confirmed according to three different situations.

Set \( n = 3 \) in the first kind of fuzzy element set:

\[
\begin{align*}
u_i (l) &= \{ (\hat{X}_i (l) - \hat{X}_j (l))^2 + (\hat{Y}_i (l) - \hat{Y}_j (l))^2 \}^{1/2} \\
u_j (l) &= \{ \hat{X}_j (l)^2 + \hat{Y}_j (l)^2 \}^{1/2} - [\hat{X}_i (l)^2 + \hat{Y}_i (l)^2]^{1/2} \\
\theta_\theta (l) &= \text{tan}^{-1} \frac{\hat{Y}_i (l) - \hat{Y}_j (l)}{\hat{X}_i (l) - \hat{X}_j (l)} - \text{tan}^{-1} \frac{\hat{Y}_i (l) - \hat{Y}_j (l)}{\hat{X}_i (l) - \hat{X}_j (l)}
\end{align*}
\]  
(6)

And the initial value of weight vector corresponding to \( U \) is set as \( a_i = 0.55, a_j = 0.35, a_i = 0.10 \).

Let \( n=5 \) in the second kind of fuzzy element set:

\[
\begin{align*}
u_i (l) &= \{ \hat{X}_i (l) - \hat{X}_j (l) \} \\
u_j (l) &= \{ \hat{Y}_i (l) - \hat{Y}_j (l) \} \\
u_i (l) &= \{ \hat{X}_i (l) - \hat{X}_j (l) \}, i \in U_1, j \in U_2 \\
u_i (l) &= \{ \hat{Y}_i (l) - \hat{Y}_j (l) \} \\
u_i (l) &= \theta_\theta (l)
\end{align*}
\]  
(7)

And the initial value of weight vector corresponding to \( U \) is set as \( a_i = 0.3, a_j = 0.3, a_i = 0.15, a_j = 0.15, a_i = 0.1 \).

Let \( n=9 \) in the third kind of fuzzy element set (8).

To the first and the second kind of fuzzy element set defined here, only the two-dimensional information is considered and it’s easy to be expanded to the three-dimensional space. What’s more, the acceleration information is not considered in these three kinds of fuzzy element set. If these elements are considered simultaneously, more fuzzy element set and initial matrix of weight vector should be constructed. Generally, the fuzzy element in track correlation can be described by the three kind of fuzzy elements set on the whole.

\[
\begin{align*}
u_i (l) &= \{ \hat{X}_i (l) - \hat{X}_j (l) \} \\
u_j (l) &= \{ \hat{Y}_i (l) - \hat{Y}_j (l) \} \\
u_i (l) &= \{ \hat{X}_i (l) - \hat{X}_j (l) \} \\
u_i (l) &= \{ \hat{Y}_i (l) - \hat{Y}_j (l) \} \\
u_i (l) &= \{ \hat{X}_2 (l) - \hat{X}_j (l) \} \\
u_i (l) &= \{ \hat{X}_j (l) - \hat{X}_j (l) \}
\end{align*}
\]  
(8)

where \( i \in U_1, j \in U_2 \), and the initial value of weight vector is set to be \( a_i = a_j = 0.2, a_i = a_j = a_i = 0.1, a_i = a_j = a_i = 1/30. \)

2) Dynamic Assignment of Fuzzy Set \( \Delta \)

Since the course information of low speed target swings in a big way, a smaller weight should be taken to the course element of low speed targets. The mutual influence among each kind of fuzzy element will be considered comprehensively by applying a dynamic assignment method to the fuzzy subset \( \Delta = (a_1(l), a_2(l), \ldots, a_n(l)) \) where \( a_i(l) \) denotes the weight corresponding to course element. In order to reduce the auto-adaptability of \( a_i(l+1) \) corresponding to the low speed target, set

\[
a_i(l+1) = a_i(l) \left[ \frac{v_j(l+1) - v_{min}}{v_{max} - v_{min}} \right]^q\]  
(9)

where \( q > 1 \) (usually set \( q = 2 \)) and \( v_j(l+1) \) is velocity of the \( i \)-th \( (i \in U_1) \) track at time \( t+1 \), \( v_{max} \) and \( v_{min} \) are the maximal and minimal velocity in the surveillance field. And then:

\[
a_i(l+1) = a_i(l) / \sum_{l = 1}^{n} a_i(l) + a_i(l+1)\]  
(10)

\[
a_i(l+1) = a_i(l+1) / \sum_{l = 1}^{n} a_i(l) + a_i(l+1)\]  
(11)

And the initial value of weight vector when \( l = 0 \) is set as \( q = 2 \). In this way, a recursion assignment process of fuzzy set \( \Delta \) is given. It can be applicable for the weight assignment with using the first and second kind of fuzzy set. To the third kind of fuzzy set, \( a_{l+1}(l+1) \), \( a_{l+1}(l+1) \), and \( a_{l+1}(l+1) \) is calculated according to (9), at the same time, \( v_j(l+1) \) and formula (10), (11) must make some corresponding adjustment. Moreover, the dynamic assignment of weight value is varied with \( i \ (i \in U_1) \). In order to reduce the
computational burden, the district processing maybe carried on during the dynamic assignment of weight vector, namely, there are \( N \) area divided on speed and \( N \) group of fuzzy subsets are calculated at first, then the selection of weight vector of the actual velocity \( v_j(l+1) \) is according to the area it located.

3) Fuzzy Binary Track Correlation Algorithms (FBTCA)

The synthesis similar degree between two tracks can be calculated after the determination of membership function, fuzzy element set and fuzzy subset \( A \). When the normally model membership function is selected, the membership of two tracks considered as similar basing on the \( k \)-th element is:

\[
\mu_k(u_i) = \exp(-\tau_k(u_i^2 / \sigma_k^2))
\]  

(12)

After membership of each element has been calculated, the synthesis appraisal may be carried on with the weighted average method. Thereupon, the synthesized similar degree can be calculated as follows:

\[
f_{ij}(l) = \sum_{k=1}^{n} a_{ik}(l) \mu_k
\]  

(13)

In this way, the fuzzy correlation matrix at time \( l \) is composed of \( n_1 \) tracks from sensor 1 and \( n_2 \) tracks from sensor 2.

\[
F(l) = \begin{bmatrix}
    f_{11}(l) & f_{12}(l) & \cdots & f_{1n_2}(l) \\
    f_{21}(l) & f_{22}(l) & \cdots & f_{2n_2}(l) \\
    \vdots & \vdots & \ddots & \vdots \\
    f_{n_1}(l) & f_{n_1}(l) & \cdots & f_{n_1n_2}(l)
\end{bmatrix}
\]  

(14)

The next step is how to perform track correlation test according to the formula (14). A maximal synthesis similar degree and threshold distinction principle are adopted here. Firstly, a maximal element \((f_{ij}(l))\) of \( F(l) \) is selected. If \( f_{ij}(l) > \varepsilon \), track \( i \) is regarded experimentally correlate with track \( j \). Then, a new fuzzy correlation matrix \( F(l) \) is obtained with deleting the line and row element to which \( f_{ij}(l) \) corresponds in \( F(l) \). During this process, the number of line and row cannot be deleted and \( F(l) \) is obtained with the same work being done to \( F(l) \). The process is persisting until all of the elements in fuzzy correlation matrix \( F(l) \) are less than \( \varepsilon \). The parameter \( \varepsilon \) is a threshold and usually is set as \( \varepsilon \geq 0.5 \). In this way, the correlation test between tracks from two sensors at time \( l \) is achieved.

Based on the double threshold detection method in the automatic radar detection theory: Two positive integers \( I \) and \( R \) are chosen, \( \forall l = 1, 2, \ldots, R \) in the correlation test, \( m_y(l) = m_y(l-1) + 1 \) and \( m_y(0) = 0 \), if track \( i \) is regarded experimentally correlate with track \( j \). Otherwise, \( D_y(l) = D_y(l-1) + 1 \). Where \( m_y(l) \) denotes the correlation mass that track \( i \) from node 1 correlated with track \( j \) from node 2 till time \( l \) and \( D_y(l) \) denotes the separation mass of tracks \( i \) and \( j \). The correlation between tracks \( i \) and \( j \) will be nearly confirmed if

\[
m_y(l-1) \geq L
\]  

(15)

The correlation test between tracks \( i \) and \( j \) would be cease at time \( l \) if only one track \( (j) \) can satisfy (15), then tracks \( i \) and \( j \) would be regarded as the correlated tracks and performed no correlation test any more. However, if there are more than one track \( (j) \) can suffice (15) the correlation test will be performed last \( l=R \) to give a precise correlation mass for the multivalency processing latter. In the same way, if

\[
D_y(l-1) > R-L
\]  

(16)

the correlation test should be ceased between tracks \( i \) and \( j \) at time \( l \). Since \( m_y(l = R) < L \) (track \( i \) and \( j \) are uncorrelated) will come into existence if \( D_y > R-L \) at time \( l-1 \). The track correlation methods based on these three kinds of fuzzy elements set are called the first, second and third fuzzy binary track correlation algorithm. In this paper, only the first and second method’s correlation performance is analyzed.

There are two situations where multivalency processing method applied, one of them is \( l=R \) and the other is \( l<R \). In case one, there are more than one track \( (j) \) suffice \( m_y(l = R) \geq L \) thus will be correlated with track \( i \). In this case, track \( j \), which maximize the track correlation mass \( m_y(l) \) will be correlated with track \( i \).

\[
\max_{j \in \{j_1, j_2, \ldots, j_q\}, m_y(l = R)} m_y(l = R)
\]  

(17)

However, if there are still more than one track can be correlated with track \( i \), the track \( j' \) will be accepted:

\[
\max_{j' \in \{j_1, j_2, \ldots, j_p\}} \|f_{ij'}(r)\| = \sum_{r=1}^{q} |f_{ij'}(r)|
\]  

(18)

After the ultimately correlation track \( j \) of track \( i \) has been confirmed, \( \forall j' \in \{j_1, j_2, \ldots, j_q\}, j' \neq j' \), if there is any experimental track \( NT \) corresponding to \( i \) or \( j \), the track \( NT \) will be deleted. The multivalency processing of case two is similar to that of case one with \( l \) replacing \( R \) in (18) and no track deleted.

4) Fuzzy Classical Assignment Rules (FCAR)

Let \( g_{ij}(l) = -f_{ij}(l) = -\sum_{k=1}^{n} a_{ik}(l) \mu_k \)

(19)

Define a binary variable as follows:

\[
\tau_y = \begin{cases} 
1 & H_o \\
0 & H_i
\end{cases}
\]  

(20)
where $H_0$ denotes that tracks $i$ and $j$ are from the same target and $H_1$ denotes that track $i$ and $j$ are from the different target. Upon that, the problem of track correlation becomes a fuzzy classic assignment problem. Namely

$$
\min \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} C_{ij} \xi_{ij}(l)
$$

(21)

The restrictive condition is given as follows:

1) If $n_1 > n_2$, $\sum_{i=1}^{n_1} \xi_{ij} \leq 1 \sum_{j=1}^{n_2} \xi_{ij} \leq 1$  

(22)

2) If $n_1 < n_2$, $\sum_{i=1}^{n_1} \xi_{ij} \leq 1 \sum_{j=1}^{n_2} \xi_{ij} \leq 1$ 

(23)

And

$$
\sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \xi_{ij} = \min(n_1, n_2)
$$

(24)

It means that only one track $j$ ($j \in U_1$) can be correlated with track $i$ ($i \in U_1$). This is named fuzzy classical assignment track correlation method. Burgeois method and the improved Munkre method can be used for the resolution of this fuzzy classical assignment problem.

The system flow chart of the proposed fuzzy binary algorithm is given in Figure. 1. Note that $E_c$, $E_e$ and $E_s$ denote the correct, error and sans correlation ratio respectively.

IV. SIMULATION

Some simulations have been run to compare the correlation performance of fuzzy binary track correlation algorithm here with the Singer’s and Bar-Shalom’s algorithm.

A. Simulation Model and Parameter Settings

There are two nodes considered in the simulations, and 2-D radar is set in each node. A Monte Carlo simulation with 50-runs was carried out for two environments. In case 1, there are 60 targets. And there are 120 targets that composed of many maneuvering, cross, and split targets in case 2. The maneuvers of these targets are random, and the initial position of these targets is normally distributed in a region. The initial velocity and azimuth of these targets is uniformly distributed in 4–1200m/s and 0–2π respectively. Let $\sigma_{\tau_1}^2 = P_{11}(i) + P_{i1}(j) + P_{33}(j) + P_{55}(j)$, $\sigma_{\tau_2}^2 = P_{22}(i) + P_{44}(i) + P_{33}(j) + P_{44}(j)$, $\sigma_{\tau_3}^2 = \pi^2 / 12$ in the first kind fuzzy element set, and the corresponding coefficient is $\tau_1 = 0.8$, $\tau_2 = 0.3$. Set

$$
\begin{align*}
\sigma_{\tau_1}^2 &= P_{11}(i) + P_{i1}(j) + P_{33}(j) \\
\sigma_{\tau_2}^2 &= P_{22}(i) + P_{44}(i) + P_{33}(j) + P_{44}(j) \\
\sigma_{\tau_3}^2 &= \pi^2 / 12
\end{align*}
$$

and $\sigma_{\tau_2}^2 = 0.5^2 / 12$ in the second kind fuzzy element set. The corresponding coefficients are set as $\tau_1 = 0.15$, $\tau_2 = 0.2$, $\tau_3 = 0.2$, $\tau_3 = 0.3$. $P_{\tau_1}(i)$ denotes the $q$-th diagonal element in the estimation covariance matrix of track $i$ at time $l$.

The state vector in (3) is $X = (x, y, y')'$, the transition matrix and noise distribution matrix is:

$$
F(k) = \begin{bmatrix}
1 & T & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & T \\
0 & 0 & 0 & 1
\end{bmatrix}
$$

$G(k) = \begin{bmatrix}
T / 2 & 0 \\
1 & 0 \\
0 & T / 2 \\
0 & 1
\end{bmatrix}
$$

(25)

where $T$ is the sample interval and $T=4$s.

The measurement vector in (4) is $Z = (x, y)'$, the measurement matrix is

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

(26)

$$
Q(k) = \begin{bmatrix}
q_{11}(k) \\
q_{12}(k)
\end{bmatrix}
$$

(27)

$$
\begin{align*}
\sqrt{q_{11}(k)} &= 15 \times 10^{-2} \hat{x}(k) \\
\sqrt{q_{22}(k)} &= 15 \times 10^{-2} \hat{y}(k)
\end{align*}
$$

(28)

The noise process standard deviations of range and azimuth measurements from each sensor are assumed to be 170 m and 0.017 rad, 180 m and 0.017 rad, respectively. The measurement noise covariance matrix is:

$$
R(k) = \begin{bmatrix}
\sigma_{\tau_1}^2(k) & \sigma_{\nu_1}(k) \\
\sigma_{\nu_1}(k) & \sigma_{\tau_1}^2(k)
\end{bmatrix}
$$

(29)

$$
\begin{align*}
\sigma_{\tau_1}^2(k) &= \sigma_p^2 \cos^2 \theta(k) + \rho^2(k) \sigma_{\nu_1}^2 \sin^2 \theta(k) \\
\sigma_{\tau_2}^2(k) &= \sigma_p^2 \sin^2 \theta(k) + \rho^2(k) \sigma_{\nu_2}^2 \cos^2 \theta(k) \\
\sigma_{\nu_1}(k) &= [\sigma_{\tau_1}^2(k) - \rho^2(k) \sigma_{\nu_2}^2 \sin \theta(k) \cos \theta(k)]^{1/2} \\
\sigma_{\nu_2}(k) &= \sigma_{\nu_2}(k)
\end{align*}
$$

where $\sigma_p^2$, $\sigma_{\nu_1}^2$ denote the noise process standard deviations of range and azimuth measurements respectively; $\rho(k)$ and $\theta(k)$ denote the range measurements and azimuth measurements respectively. Assuming that all of these measurements have been associated to the tracks correctly, the initial setting of filter is given as follows:

$$
\begin{align*}
\hat{X}(1|1) &= z_1(1), & \hat{X}(1|1) &= [z_1(1) - z_i(0)] / T \\
\hat{Y}(1|1) &= z_2(1), & \hat{Y}(1|1) &= [z_2(1) - z_i(0)] / T
\end{align*}
$$

(30)

$$
P(1|1) = \begin{bmatrix}
\sigma_{\tau_1}^2(1) & \sigma_{\nu_1}(1) & \sigma_{\tau_1}(1) \\
\sigma_{\nu_1}(1) & \sigma_{\nu_1}(1) & 2\sigma_{\tau_1}(1) \\
\sigma_{\tau_1}(1) & 2\sigma_{\tau_1}(1) & \sigma_{\nu_1}(1)
\end{bmatrix}
$$

(31)
B. Simulation Results and Analyses

When $\varepsilon = 0.7$ and the normally model membership function is used, table 1 and table 2 show $E_c$, $E_e$ and $E_s$ of Singer’s, Bar-Shalom’s and the proposed algorithms in case 1 and case 2, respectively. Figure 2 and Figure 4 give the results of correct correlation ratio (CCR) of each algorithm varying with time step in case 1 and case 2, respectively. Figure 3 and Figure 5 show the error correlation ratio (ECR) varying time step.

From these simulation results we can find that the correlative performance of Bar-Shalom’s algorithm is a little better than that of Singer’s algorithm and the correlative performance of the proposed algorithms is much better than that of Singer’s and Bar-Shalom’s algorithm, especially in case 2 where dense and maneuvering targets exist. Specifically, the largest improvement ratio of $E_c$ reaches about 35%. The fuzzy correlation criterions and the double threshold detection method are key factors for improving correlative accuracy.
FBTCA/FCAR is a litter better than that of the first shown that the correlation performance of the second FBTCA is a little than that of the second FBTCA. It can be explained by To compare the relative performance of the proposed algorithm are proposed in this paper. Firstly, fuzzy and the double threshold detection method from the consists in its adaptability and scalability in such systems better than that of the first FCAR and the first FBTCA correlative performance of the second FBTCA is a little (Notice: \( N \) denotes the number of target in the common surveillance, and the normally model membership function is used)

<table>
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<tr>
<th>Ec</th>
<th>Bar-Shalom’s algorithm</th>
<th>First FBTC</th>
<th>Second FBTC</th>
<th>Ec</th>
<th>Bar-Shalom’s algorithm</th>
<th>First FBTC</th>
<th>Second FBTC</th>
<th>Ec</th>
<th>Bar-Shalom’s algorithm</th>
<th>First FBTC</th>
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</table>

However, the above simulation results also have shown that the correlation performance of the second FBTC/FCAR is a litter better than that of the first FBTC/FCAR. That is mainly because that the fuzzy processing ability of the second FBTC/FCAR is stronger than the first ones and it affects correlative operation directly.

To compare the relative performance of the proposed FBTC with that of FCAR distinctly, the Cauchy model membership function is used in the FBTC and the normally model membership function is used in the FCAR. Table 3 and table 4 show \( E_c, E_e \) and \( E_r \) of each algorithm in case 1 and case 2, respectively. Figure.6 and Figure.8 give the results of CCR of each algorithm varying time step in case 1 and case 2, respectively. And the corresponding ECR are shown in Figure.7 and Figure.9 respectively.

As shown in the above simulation results, the correlative performance of the second FCAR is better than that of the second FBTC. It can be explained by that FCAR achieves higher correlative accuracy with sacrificing computation consuming. Meanwhile, the correlative performance of the second FBTC is a little better than that of the first FCAR and the first FBTC achieves the worst correlative performance of four proposed algorithms. In spite of this, FBTC still improve correlative accuracy obviously of the two traditional algorithms.

Moreover, all of these proposed algorithms still have consistent performance even the scenario is so complex that lots of dense and maneuvering targets exist, as in simulation of case 2. It should be noted that another advancement of the proposed fuzzy binary algorithms consists in its adaptability and scalability in such systems which contain some large navigation error, sensor adjustment error, conversion error or delay error.

V. CONCLUSION

Based on the maximal synthesis similar degree, threshold distinction principle from fuzzy mathematics and the double threshold detection method from the automatic radar detection theory, the fuzzy binary track correlation algorithm and the fuzzy classical assignment algorithm are proposed in this paper. Firstly, fuzzy

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element set and the corresponding membership function is established. And then, the selection of fuzzy element and initial weight vector in track correlation is discussed. Meanwhile, fuzzy binary correlation criterions and the system flow of fuzzy binary track correlation algorithm are presented in detail. Finally, the correctness and the validity of proposed algorithms are proved in a representative simulation. According to the simulation results, the performances of algorithms mentioned in this paper don’t distinguish obviously when there are only a few normal targets in surveillance. However, the advantage of proposed algorithms will become apparent as the environments getting more and more complex. Thus, the proposed fuzzy binary algorithms present a better general correlative performance in hybrid scenarios such as dense and maneuvering targets. Especially, in the scenarios with large navigation error, sensor adjustment error, conversion error and delay error, the proposed algorithms can show strong robustness because of its fuzzy processing ability. Moreover, another advancement of the fuzzy binary algorithms consists in their adaptability to the systems that can’t offer estimation covariance.

In this subsection, all of the membership function is regarded as normally model.
In this subsection, the membership function of the FBTCA is regarded as cauchy model and the normally model is used in the FCAR.

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REFERENCES


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