A Multiple FCMs Data Association based Algorithm for Multi-target Tracking

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Abstract: Multi-target tracking is a key problem in the field of multi-sensor data fusion. A novel algorithm of Multitarget tracking based on multiple FCMs data association is proposed for the Multi-sensor Multi-target (MSMT) tracking system. The algorithm can make full use of the information embedded in the measurements of sensors, make the minimization of the variance of the measurement fusion value through a linear weighting, and with a great reduction of the tracking errors caused by the association errors. Then the flow diagram is presented. In a scenario having five sensors and five targets, the simulation results show that the proposed algorithm has the advantages over the existing ones of simplicity and efficiency.

Key words: MSMT Tracking, Data Association, Fuzzy C-mean Clustering (FCM)

1. Introduction

A significant problem in the MSMT tracking systems is measurement-to-track association. A number of approaches have been proposed in the literature to solve this problem. For example, the nearest neighbor filter (NN), the probabilistic data association (PDA) and the joint probabilistic data association (JPDA) techniques [3,5,6]. Recently, Singh and Bailey [1] developed the first fuzzy logic approach to the data association based on the fuzzy knowledge-base (IF THEN rules). Unfortunately, their approach to the case of more than three or four targets is computationally infeasible due to the large number of rules. Asharf M.Aziz[2] developed a nearest-neighbor fuzzy logic data association approach based on the fuzzy c-means clustering algorithm(FCM), achieved the improvement of computational complexity and performance.

In this paper, an algorithm of multi-target tracking based on multiple FCM data association is presented for Multi-sensor Multi-target (MSMT) tracking system. The algorithm can make the best of the information

available of the measurements received from the sensors, and reduce the tracking errors caused by the association errors. Finally the flow chart of the algorithm is given.

The paper is organized as follows. The problem of multitarget tracking is formulated in Section 2. The proposed multiple FCMs data association algorithm is presented in Section 3. Section 4 described The measurement fusion method. Simulation results are given in Section 5. Conclusions are presented in Section 6.

2. Problem Formulation

a. The Measurement Model

Our problem formulation follows the work of Asharf M.Aziz[2]. We assume that there are T targets(T known) in the surveillance region. We allow missed detections and false alarms in our problem formulation. The measurement noises are assumed to be independent across the sensors, $m_{k_i} (i=1,2,\dots,N)$ is the number of the measurements from the sensor i at time k. In a multi-sensor environment, the measurement equation is given by

$$Z_l^i(k) = H_i(k) X^t(k) + W_i^t(k), \\ t = 1, 2, \dots, T; l = 1, 2, \dots, m_{k_i} \quad (1)$$

where $Z_l^i(k)$ is the measurement from the target t at time k. $H_i(k)$ is a known matrix and the measurement noise $W_i^t(k)$, is assumed to be normally distributed with mean zero and known variance. Denote the set of validated measurements from all the sensors at time k as

$$Z(k) = \{Z^i(k)\}_{i=1}^N, \quad Z^i(k) = \{Z_l^i(k)\}_{l=1}^{m_{k_i}} \quad (2)$$

b. FCM Data Association Algorithm (FCMDA)

Suppose that n measurements are received at time k in a MSMT environment. For simplicity, we assume that z_l ($l = 1, 2, \dots, n$) denote the measurement sequences. The number of measurements n does not necessarily equal the number of targets c . It is required to assign only one of the n measurements to each target such that each measurement can have only one origin. Our goal is to associate each measurement z_l with one of c possible tracks given predicted values v_i for each track i , $i = 1, 2, \dots, c$. The targets predicted values v_i can be estimated using the Kalman filtering techniques.

The FCM data association includes the following steps:

Step 1: Apply the FCM algorithm for a fixed $V(v_1, v_2, \dots, v_T)$ and find the partition matrix U [2,7],

which represents the degrees of membership of all measurements to all tracks. The association matrix U represents the assignment matrix between all measurements and all targets. Each element in the partition matrix u_{ik} ($i = 1, 2, \dots, c, k = 1, 2, \dots, n$) represents an association measure between the predicted value of track i and measurement k .

Step 2: Search for the maximum degree of membership $u_{i_M k_M}$ (the closest measurement-to-track pair) and make the indicated assignment, associate measurement k_M to track i_M .

Step 3: Remove the measurement-to-track pair identified above from the assignment matrix U and obtains the reduced matrix.

Step 4: Repeat step 2 and 3 for each remaining track until c measurements are assigned to the c existing tracks.

Step 5: Obtain the final assignment of measurements to tracks.

Asharf M.Aziz [2] applied this approach to the case of a two-dimensional MSMT tracking system. The approach performs 96.67% with respect to perfect

correlation. It is shown that this approach is feasible, simple and effective in the MSMT tracking system.

3. Multiple FCMs Data Association Algorithm (M-FCMDA)

In the conventional FCM data association algorithm, we can see that target state vector is updated only by the measurement of the maximum degree of membership. As a result, under the environment of low-SNR (Signal-to-Noise Ratio) and high density of returns, there are decreases both of the probability of association and the ability of anti-jamming. In order to overcome this problem and take the best of the available measurement information received from the sensors, we proposed a new algorithm of multi-target tracking based on multiple FCMs data association (see Fig. 1).

In the flow diagram show in Fig.1, first, single FCM data association that associates the observations $(Z_j^n(k))_{j=1}^{m_{k_i}}$ from the sensor n with all the targets is made independently across the sensors, thus we can acquiring N lists S_n ($n = 1, 2, \dots, N$) of association, where S_n denote the list of target j associated with its corresponding measurement $Z_j^i(k)$ based the FCM data association. In the list S_n , s_{nt} denotes the association that the measurement is assigned to the target t . Then, a measurement fusion values $\hat{Z}^t(k)$ ($t = 1, 2, \dots, T$) can be acquired (the method of measurement fusion is introduced in the following section). Finally the fusion value $\hat{Z}^t(k)$ is considered as the candidate measurement value to update the target t state by using the kalman filtering.

Figure 1. Multiple FCM data association algorithm

4. Measurement Fusion and Target Tracking

The measurement noises are assumed to be

independent across sensors. and $\sigma_w(i)$ ($i=1,2,\dots,N$) are assumed unequal to each other. The measurement fusion problem of target t is given by:

$$\hat{Z}^t(k) = \sum_{i=1}^N a_i Z_i^t(k) \quad (3)$$

subject to

$$\sum_{i=1}^N a_i = 1 \quad (4)$$

It is easy to prove that the fusion value $\hat{Z}^t(k)$ is unbiased. In order to minimize the deviation of errors of the fusion values [4], the fusion rule is defined as follows:

$$J = \min \sum_{i=1}^N a_i^2 \sigma_w^2(i) \quad (5)$$

subject to

$$\sum_{i=1}^N a_i = 1 \quad (6)$$

Using the Lagrange multiplier method, the results of this minimization are given by

$$a_i = 1 / \left(\sigma_w^2(i) \sum_{j=1}^N \frac{1}{\sigma_w^2(j)} \right), \quad \sigma_{z'}^2 = N / \sum_{j=1}^N \frac{1}{\sigma_w^2(j)},$$

where a_i denote the Lagrange multipliers, $\sigma_{z'}^2$ the

deviation of fusion value $\hat{Z}^t(k)$. Thus the target t predicted and estimated values can be obtained using the kalman filtering based on the fusion values $\hat{Z}^t(k)$.

$$\hat{X}^t(k+1/k+1) = \Phi^t(k) \hat{X}^t(k/k) + K(k+1) r^t(k) \quad (7)$$

$$K(k+1) = P^t(k+1/k) H_i^T [H_i^t P^t(k+1/k) H_i^T + \sigma_{z'}^2]^{-1} \quad (8)$$

$$P^t(k+1/k) = \Phi^t(k) P^t(k/k) \Phi^t(k) + G^t(k) Q G^t(k)^T \quad (9)$$

$$P^t(k+1/k+1) = [I - K(k+1) H_i] P^t(k+1/k) \quad (10)$$

$$r^t(k) = \sum_{i=1}^N a_i Z_i^t(k) - H_i \Phi^t(k) \hat{X}^t(k/k) \quad (11)$$

5. Simulation Results

A scenario having five sensors and five targets is considered. The target's motion model is assumed to be:

$$X(k+1) = \Phi X(k) + V(k) \quad (12)$$

where

$$\Phi = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (13)$$

The state vector $X(k)$ contains the target's positions and velocities in x and y directions: $X(k) = (x(k) \ v_x(k) \ y(k) \ v_y(k))$. The measurement equation is (1), the measurement matrix

$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$, the noise sequence $W_i^t(k)$ has

covariance matrix $R = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix}$, where σ_x^2 and

σ_y^2 ($\sigma_x^2 = \sigma_y^2$) are the variances of the measurement errors in x and y position respectively. The overall mean estimated error is computed by

$e = \sum_{i=1}^T \sqrt{(\hat{x}^i - x_{true}^i)^2 + (\hat{y}^i - y_{true}^i)^2} / T$. T is the number of the targets.

In this example, we consider an ideal situation in which all the targets are detected by every sensor and all the measurements come from targets only. The initial positions and speeds of the targets are [6000 6000 6000 6000 6000; 100 100 100 99.2 100.1; 6000 6100 5900 6350 5650; 0 0 0 -35.4 35.1]. The standard deviations of positions and speeds are different from each target. Fig.2 shows the result of tracking based on processing 20 measurements (20 seconds) each sensor over a 100-run Monte Carlo simulation. Fig.3 shows the results of the overall mean estimated error of conventional FCM association approach, with processing 200 measurements (20 seconds) each sensor over a 50-run Monte Carlo simulation. Fig.4 show the results of tracking using the proposed approach and perfect data association. The perfect data association represents the correct association between all received measurements and all targets and determines the lower

bound of the estimation error. The results show that the proposed approach successfully tracks five targets and have better performance than the conventional approach and a reasonable performance with respect to perfect data association.

Fig. 2. Actual and Mean Estimated Tracks

Fig. 3 Mean Estimated errors:FCM data association

Fig. 4. Mean Estimated errors: the proposed approach and perfect data association

An algorithm based on multiple FCM data association is proposed for multi-target tracking. Based on the multiple FCMs data association and measurement fusion, the algorithm can utilize the most useful measurements of the same target from the sensors, make the minimization of the variance of the measurement fusion value through the linear weighting, and reduce the tracking errors caused by the association errors. The flow diagram is given. Simulation results show the performance of this approach is better than the conventional approach, and achieve the requirement of multi-target tracking.

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6. Conclusion