Asynchronous Multisensor Track Association Algorithm and Simulation

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Abstract
In the multisensor information system, the local track from different sensors is often asynchronous. According to this problem, this paper presented a multisensor asynchronous track association algorithm based on pseudo measurement. Firstly, the technology of pseudo measurement is used to synchronize tracks. Then local tracks are assigned by using classical assignment algorithm, so as to achieve the purpose of asynchronous association. The simulation results prove that this method can well solve the multisensor asynchronous association, and the association correct probability close to 90%.

Keywords: multisensor; asynchronous track association; pseudo measurement; simulation

1. Introduction
Multisensor data fusion is comprehensive handling multisensor information, thus produce new meaningful information[1], and this information is not available in any single sensor. This handling technology in many areas of military and civilian applications has been typical of many successful cases. In recent years, it is subject of great concern. Multisensor information fusion system architecture is divided into two kinds of centralized and distributed. In the centralized fusion system produces track in the fusion center; in distributed fusion systems generates track in the local node. Whatever multisensor information fusion system uses what structure, to realize the automatic comprehensive information, an important issue is how to associate tracks from different local node, and how to identify the original track from the same goal[2,3].

Previous research in track association has focused on synchronous association, that is to assume that the target of each sensor measurement is carried out simultaneously, and transmit data to the fusion center is synchronized. In actual practice, often encountered in the association is asynchronous problem. In
system, a variety of sensors have different sampling rates and different communication delays, which will have an asynchronous multisensor data fusion problem.

This paper presents a method that unifies different measurements and filtering value to the same moment using trace reconstruction [1]. Research does not consider communication and computing delays. Simulation results show the effectiveness and feasibility of the algorithm.

2. Formation of local tracks

In the information fusion system With M sensors, assuming that its public surveillance area has N targets, the state equation of target j is

\[ X^i(k+1) = \phi_i(k+1,k)X^i(k) + W_i(k) \quad i=1, 2, ..., N \]  

(1)

Where \( X^i(k) \) is the state of target i, and \( W_i(k) \) is a zero mean Gaussian process with covariance

\[ E[W_i(k)W_i^T(j)] = Q_{ij} \sigma_{kj} \]  

(2)

The measurement model for target i is given by

\[ Z^i(k) = H_jX^i(k) + V^i_j(k) \]  

(3)

Where \( H_j \) is measurement matrix, and \( V^i_j(k) \) is a zero mean Gaussian process with covariance.

\[ E[V^i_j(k)V^T^i_j(j)] = R_{ij} \sigma_{kj} \]  

(4)

The structure of the feedback fusion system is given in figure (1). The two sensors are assumed to have different sampling rates and different communication delays. Assume that each sensor processes its observations locally and communicates its track to a fusion center. The central processor fuses the track of both sensors and communicates the fused track back to each sensor. Each sensor implements a Kalman filter to track the target. Let \( \hat{X}^i(k,k) \) and \( \hat{P}^i(k,k) \) be the track produced by the fusion center at time \( t = kT \), where \( T \) is the update period of the fused track. It is worth noting here that \( T \) can be variable to accommodate communication delays and or to allow the central computer to finish its commitment to a prior task before it can update the fused track. Let \( \hat{X}^i_j(k+1,k+1) \) and \( \hat{P}^i_j(k+1,k+1) \) be the track provided by sensor j, j = 1, 2.

At every local update period, each sensor uses the previous output of the fusion center as its initial track. In this case, at time k+1, the updated track of sensor j is given by

\[ \hat{X}^i_j(k+1,k+1) = \phi_j(k+1,k)X^i_j(k,k) \]

\[ +K_j^i[Z^i_j(k+1) - H_j^i\phi_j(k+1,k)X^i_j(k,k)] \]

\[ \hat{P}^i_j(k+1,k) = \phi_j(k+1,k)P_j^i(k,k)\phi_j(k+1,k)^T \]

\[ +Q_j(k) \]  

(5)

(6)

Completed all the local sensors for multiple target tracking filter, and the results into the fusion center, a practical problem is that the data is often the case in the local sensors receive asynchronous. So the problem must be solved is how to unity measurements and filtering value coming from different sensor to a point, which is the time calibration problems.
3. Time calibration using pseudo measurement

Multisensor system (such as airspace surveillance system) composed by several radar. According to the command and control, these radar must randomly start working, and can not synchronize the boot or scanning from the north direction. In addition, the scanning rate in the actual work of sensors is not constant for the same. Therefore, on multisensor track-to-track correlation time calibration is necessary before[4].

Pseudo measurement was not the actual point given by radar or sensors track, not estimates, but the value of a particular point in time derived by estimated value and the filtering equation, and the derivation process is the point of track reconstruction. If after a certain time interval, the fusion center took all the estimate of local sensors are reconstruction to an appropriate time points, it would be the time calibration at this time point. As shown in figure 1 below.

\[\hat{X}_1^j(T_k, T_{k-1}) = \phi_1^j(T_k, t_m)X_1^j(T_k, t_m) + K_1^j[Z_1^j(T_k) - H_1^j(\phi_1^j(T_k, t_m)X_1^j(T_k, t_m))]\]  \hspace{1cm} (7)

Where \(Z_1^j(T_k)\) is the observation point for updating the \(j\) local track, by solving the above equation can obtain

\[Z_1^j(T_k) = H_1^j(\phi_1^j(T_k, t_m)X_1^j(T_k, t_m)) + (K_1^j)^{-1}[(\hat{X}_1^j(T_k, T_k) - \phi_1^j(T_k, t_m)X_1^j(T_k, t_m))]\]  \hspace{1cm} (8)

Track reconstruction requires track state estimate \(\hat{X}_1^j(T_k, T_k)\), the state transition matrix \(\phi_1^j(T_k, t_m)\), filtering gain matrix \(K_1^j\) and measure matrix \(H_1^j\). Estimate \(\hat{X}_1^j(T_k, T_k)\) is already in the fusion center, and \(\phi_1^j(T_k, t_m)\) is a constant \(\phi_1\). If the local sensors can achieve the full Kalman filter, and have enough information about the local processing, the fusion center will be able to calculate the gain matrix \(K_1^j\).

\[K_1^j = P_1^j(k/k-1)H_1^j(S_1^j(k))^{-1}\]  \hspace{1cm} (9)

Where the matrix \(S_1^j\) is defined by

\[S_1^j = H_1^jP_1^j(k/k-1)H_1^jT + R_1^j\]  \hspace{1cm} (10)
\[ P_1^i(k) = \phi_1^i(k \mid k)P_1^i(k-1 \mid k-1)(\phi_1^i(k \mid k))^T + Q_1^i(k) \]  
(11)

\[ P_1^j(k) = P_1^j(k \mid k-1) - K_1^j(k)S_1^j(k)(K_1^j(k))^T \]  
(12)

In tracking systems using Kalman filter, if the global processor insufficient information available, you need to put gain matrix from the local processor to the fusion center, so that the fusion center using the track reconstruction technique. Using the same method can calibrated the time of the sensor LP2 to the \( T_k \) point. If the system of sensors is more than two number, and the rest can be handled this way.

4. Track Association

Currently, a large number of domestic and foreign scholars to study the theory and method of track correlation. The usual method is to set the constraints first, and then find the optimal solution in the global scope, in order to improve the accuracy of track association. In this paper, this approach was adopted.

Assuming the track of local node(LP1, LP2) were the following form

\[ U_1 = \{1, 2, \cdots, n_1\}, \quad U_2 = \{1, 2, \cdots, n_2\} \]

\[ t_{ij}(k) = \hat{X}_1^i(k \mid k) - \hat{X}_2^j(k \mid k) \]  
(13)

\( t_{ij}(k) \) is the distance between track \( i \) of LP1 and track \( j \) of LP2, and its covariance is

\[ C_{ij}(k) = E[t_{ij}(k)t_{ij}(k)'] = P_i^j(k \mid k) + P_j^j(k \mid k) \]  
(14)

Use these elements can form a 3 dimensional statistical distance matrix \( \alpha(k) \). Thus, the above issues constitute the integer programming problem:

\[ \text{Min } L(k) = \sum_{i=1}^{N} \sum_{j=1}^{N} \eta_{ij} \rho_{ij}(k) \]  
(15)

Constraint conditions is

\[ \sum_{i=1}^{N} \eta_{ij} = 1, \quad \forall j \in \{1, 2, \cdots, N\} \]  
(16)

\[ \sum_{j=1}^{N} \eta_{ij} = 1, \quad \forall i \in \{1, 2, \cdots, N\} \]  
(17)

Constraint conditions means that a track of local node 1 can only associated with a track of local node 2, or associated with the virtual target track. The method of Munkre can be used to solve the integer programming problem.

5. Simulation and Performance Analysis

Suppose there are two sensors tracking four targets simultaneously, and the sensor is a 2D radar, shown in Figure 2. Sensors continue to track the target 60s, and this simulation carried out 100 times.
Case 1: The distance and angle error of LP1 is $\sigma_{r1} = 400\text{m}, \sigma_{\theta1} = 0.02\text{rad}$, Sampling time $t_1 = 1\text{s}$; The distance and angle error of LP2 is $\sigma_{r2} = 400\text{m}, \sigma_{\theta2} = 0.02\text{rad}$, Sampling time $t_2 = 1\text{s}$. Sampling time of fusion center $t = 3\text{s}$. LP2 and LP1 started simultaneously.

Case 2: The distance and angle error of LP1 is $\sigma_{r1} = 400\text{m}, \sigma_{\theta1} = 0.02\text{rad}$, Sampling time $t_1 = 0.9\text{s}$; The distance and angle error of LP2 is $\sigma_{r2} = 200\text{m}, \sigma_{\theta2} = 0.015\text{rad}$, Sampling time $t_2 = 0.8\text{s}$. Sampling time of fusion center $t = 3\text{s}$. LP1 start later than LP2 10 seconds.

For evaluating the Effects of track association, there are two types of probability: the first category is the correct association probability, that the objectives of the two tracks from the same sentence as the associated probability; second category is the error association probability, that the objectives of the two tracks from the different sentence as the associated probability.

In case 1, two sensors is simultaneously, and the method for track association in the simulation given by literature [5,6] was used. Figure 3 shows the correct association probability curve. Due to the classic assignment method is in certain constraints in the global scope, for the optimal solution to problems, so improved correct association probability. In Figure 4, this method is less than weighting method in error association probability.

In case 2, two sensors is asynchronous, that is typical of multisensor asynchronous association problem. In the simulation, asynchronous track time is calibrated using pseudo measurement first.

The simulation results show that both the classic assignment method or the weighted method, the quality of track association did not decreased significantly, and correct association probability close to 90%, as shown in Figure 5 and Figure 6.

6. Conclusion

This paper mainly studies the multisensor track association problem in cases of asynchronous. Papers discussed the method of time calibration using pseudo measurement in detail, then used the classic assignment method for matching the local track. For the case of two local sensors, the specific calculation process is given, and the simulation in both cases is given. The simulation result illustrates that this new algorithm can solve the problem of asynchronous track association effectively, and the association correct rate than synchronous association in the same circumstances only low by about 5%. For the case of multiple local nodes, the methods of multi-dimensional distribution can be used for track association.
References


