A New Data Association Algorithm for Multi-target Tracking in a Cluttered Environment

Y. M. Chen
Dept. of Industrial Engineering and Management, Yuan Ze University , Taoyuan, Taiwan, ROC..
chenyeeming@saturn@yzu.edu.tw

Abstract – This paper presents a new multi-target data association algorithm for radar tracking which we call the Fuzzy data association (FDA). This approach is formulated using the extended Kalman filter and FDA is accomplished using the fuzzy logic algorithm. Simulation results for heavily cluttered conditions show that the tracking performance of the proposed algorithm is better than the probabilistic data association (PDA) or the joint probabilistic data association (JPDA) filter.

Keywords: Data association, Multi-target tracking, Fuzzy logic.

1 Introduction

Most methods of the multi-target tracking (MTT) algorithm have been developed for the traffic applications. However, the maneuvering conditions of vehicles, the clutters within in surveillance radar areas become a quite difficult tracking problem [1,2]. The design of a practical MTT algorithm in such a surveillance environment poses a challenging and exciting problem.

The one difficulty in MTT is data association (DA)[4], especially in maneuvering targets tracking in the clutter environment. The probabilistic data association (PDA) [3] and joint probabilistic data association(JPDA) [5] are conventionally used along with a bank of Kalman filters. However, in either dense target or cluttered environment, radar observations are degraded, thus degrading the target tracking performance.

The probabilistic data association (PDA) is sub-optimal Bayesian algorithm which assumes that there is only one target of interest and whose track has been initialized. Given N observations, \( z_j(k), j=1,2,...,N \) within the validation gate of the track \( i \) at the \( k \)th scan, The PDA forms N+1 hypothesis \( H_j \). The first hypothesis, \( H_0 \), is the case in which none of the N observations is originated from the track \( i \), and \( H_j (j > 0) \) denotes the hypothesis that \( j \)th observation is originated from the track \( i \). The state updating in the PDA uses the combined innovation defined as

\[
v_i(k) = \sum_{j=1}^{N} \beta_{ij} v_j(k)
\]

where

\[
\beta_{ij} = \frac{a_{ij}}{a_{i0} + \sum_{j=1}^{N} a_{ij}}
\]

\[
a_{i0} = \frac{(2\pi)^{M/2}}{\lambda \sqrt{\det(S_i(k))}} (1 - P_D P_G)/P_D\]

\[
a_{ij} = \exp\left[-\frac{1}{2} v_j^T(k) S_i^{-1}(k) v_j(k)\right]
\]

and \( P_D \) is the probability of target detection, \( P_G \) the probability of a target return falling within the validation gate, \( S \) the innovation covariance, \( \lambda \) the clutter density and \( M \) the dimension of the measurement vector. Now define the combined innovation as the weighted sum of the residual associated with the \( N \) observation. Then, the target tracking algorithm using the extended Kalman filter updating its state vector, which is formed by position and velocity, are given by

\[
\hat{x}_i(k | k) = \hat{x}_i(k | k-1) + K_i(k) v_i(k)
\]

The estimated error covariance matrix, associated with \( \hat{x}_i(k | k) \), is given by

2. Preliminaries

2.1 Probabilistic data association
\[
\hat{P}_i(k | k) = \beta_{10}(k) \hat{P}(k | k-1) + [1 - \beta_{10}(k)] P_i^c(k | k) + \bar{P}_i(k)
\] (3)

where:

(I) \( P_i^c(k | k) = \mathbb{I} - K_i H_i(k) \hat{P}_i(k | k-1) \) (3a)

(II) \[ \hat{P}_i(k) = K_i(k) \sum_{j=1}^{N} \beta_{ij}(k) v_{ij}(k) v_{ij}^T(k) - v_{ij}(k) v_{ij}^T(k) \mathbf{I}_i(k) \] (3b)

(III) \( \beta_{10} \) is the probability that all measurements in the validation gate of track \( i \) are false.

(IV) \( H_i(k) \) is the linearization measurement matrix for target \( i \).

(V) \[ P_i(k | k-1) = F_i(k-1) \hat{P}_i(k-1 | k-1) + \tilde{Q}_i(k) \] (3c)

where \( F_i(k) \) is the transition matrix and \( \tilde{Q}_i(k) \) the process noise covariance matrix, both of target \( i \).

The Kalman filter gain is

\[
K_i(k) = \hat{P}_i(k | k-1) H_i^T(k) S_i^{-1}(k)
\] (4)

### 2.2 Joint probabilistic data association

In the calculation of \( \beta_{ij} \), the PDA assumes that all the tracks are isolated and does not take into account the possibility that some observations in the gate may come from other targets. For the JPDA, the probability of track \( i \) being associated with observation \( j \), is the sum of the probabilities of all joint events, \( \theta(k) \), in which track \( i \) is associated with observation \( j \), which can be expressed as

\[
\beta_{ij}(k) = \sum_{\theta(k)} P[\theta(k) | Z^K] \omega_{ij}[\theta(k)]
\] (5)

where \( \omega_{ij}(\theta(k)) \) is a binary variable indicating whether track \( i \) is associated with association \( j \) in the event \( \theta(k) \).

The probability of the event \( \theta(k) \) given \( Z^K \), the set of all the observations received up to the current scan \( k \), is given by [3]:

\[
P[\theta | Z^K] = \frac{1}{C} \frac{n!}{n_1! n_2! \cdots n_N!} \prod_{j=1}^{N} [N(e_j(k))]^{n_j} \prod_{i=1}^{N} (P_{ij})^{n_i} (1 - P_{ij})^{n_i - n_j}
\] (6)

where \( C \) is a normalization constant, \( V \) the gate volume, \( n \) the number of observations determined to be clutter in \( \theta(k) \), and \( N[e_j(k)] \) is the normal probability density function with zero-mean and a covariance matrix equal to that of \( e_j(k) \). Define two quantities, \( \tau_j \) and \( \delta_i \), such that \( \tau_j \) is equal to one if the \( j \)th observation is assigned to a track in the event \( \theta(k) \) and zero otherwise, and \( \delta_i \) is equal to one if the \( i \)th track has been assigned an observation in \( \theta(k) \) and zero otherwise. Assuming a Possion density for clutter points, the probability of the event \( \theta(k) \) given the history of observations up until scan \( k(Z^K) \), The Kalman filter is updated using the same set of equations as in the PDA.

The JPDA approach provides an optimal data association solution in the Bayesian framework. However, the number of possible hypothesis associating different returns to targets in the JPDA increases rapidly with the number of targets and the presence of clutter. Consequently, the JPDA approach requires a prohibitive amount of processor time calculating the joint probabilities even for a small number of targets in light dense clutter. To solve this problem, the alternative methods of JPDA should be further study, the determination of the magnitude of the covariance matrix for the system modeling uncertainty, the discretion of a lot of non-target interference and/or a high level of background noise level. By applying a fuzzy logic technique(7,8,9) to the multitarget tracking environment it will be able to create a robust tracking system that is capable of maintaining signal lock on the target even in a highly cluttered environment.

### 3. The fuzzy tracking system

Fundamentally, the conventionally tracking techniques are too restrictive to deal with the complexity of tracking problem. There is a very sharp demarcation line between target and non-target at the gate boundary. This type of target classification clearly does not reflect too well. By incorporating human-like reasoning into the tracking problem, results comparable to the JPDA can be achieved. Figure 1. shows the architecture of the fuzzy tracking system. It consists of the following function blocks.

(1) EKF is the standard suboptimal extended Kalman filter that gives values of state estimates and their covariances. Inputs are the state estimate vector \( \hat{x} \), its covariance matrix \( \hat{P} \), and the measurements vector \( \mathbf{z} \).

(2) Fuzzy data association (FDA) was used to evaluate the association degree between the return and the actual interest (not clutter or other
targets. Inputs are the measurement innovation, which based on the availability of objective and/or heuristic. We use the FDA approach instead of the JPDAF approach. Namely, the state estimate is then adjusted according to

$$\hat{y}^F_j(k) = FDA(\theta, A, \Phi)$$

(7)

**FDA** is a fuzzy function, which is used to evaluate the association degree $\hat{y}^F_j$ based on the set of membership functions $A$ and the set of proposition $\Phi$. Thus, the FDA keep the main idea of the JPDA, but can incorporate additional information or heuristic rules. Using fuzzy logic methodology, the rules in the FDA rule base are evaluated. The FDA rules to determine the degree of association are the form in (8).

$$R1: \text{If } \tilde{Z}_R \text{ is NL and } \tilde{Z}_\theta \text{ is NL Then } \hat{y}^F_j = VL$$

$$R2: \text{If } \tilde{Z}_R \text{ is NL and } \tilde{Z}_\theta \text{ is NM Then } \hat{y}^F_j = VL$$

$$R3: \text{If } \tilde{Z}_R \text{ is NL and } \tilde{Z}_\theta \text{ is NS Then } \hat{y}^F_j = ML$$

$$\vdots$$

The fuzzy variable, FDA, has 49 If-Then rules which are provided in Table 1. In this table, the fuzzy term set of input variables were given by \{NL, NM, NS, Z, PS, PM, PL\} where NL, NM, NS, M, PS, PM and PL denote Negative Large, Negative Medium, Negative Small, Zero, Positive Small, Positive Medium, and Positive Large, respectively. The fuzzy term set of output variables was \{VL, ML, M, MH and VH\}, which denote very low, medium low, medium, medium high, and very high, respectively.

<table>
<thead>
<tr>
<th>Association degree</th>
<th>Range Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>degree</td>
<td>NL</td>
</tr>
<tr>
<td>NL</td>
<td>VL</td>
</tr>
<tr>
<td>NM</td>
<td>VL</td>
</tr>
<tr>
<td>NS</td>
<td>ML</td>
</tr>
<tr>
<td>Z</td>
<td>M</td>
</tr>
<tr>
<td>PS</td>
<td>ML</td>
</tr>
<tr>
<td>PM</td>
<td>VL</td>
</tr>
<tr>
<td>PL</td>
<td>VL</td>
</tr>
</tbody>
</table>

4. Simulation results

A comparison of track performance for the PDA, JPDA and FDA algorithms is presented in this section. The main focus of the simulation study is to compare various tracking algorithms when applied to track maintenance a highly maneuvering target in the presence of clutter. Clutter densities from $2 \times 10^{-4}$ to $16 \times 10^{-4} /m \times mrad$ are employed in the simulation study, and referred to as light and heavy. The radar sensor provides range and azimuth measurements to the tracking algorithm, which estimates the position and velocity of the target in the horizontal plane.

The performances of the tracking algorithms are compared by 200 Monte Carlo simulation runs. The two maneuvers with minimum separation distance flight scenario were chosen from the benchmark problem for maneuvering targets. The measurement noises are zero mean Gaussian with a standard deviation of 120m for range and 5mr for azimuth and elevation angles. The sample rate is 1 Hz.

4.1 Configurations
The FDA is presented to demonstrate the feasibility of using fuzzy logic for maneuver detection and data association in highly cluttered environment.

For the FDA configurations, the sets of membership functions which fuzzify these crisp inputs, defined over appropriate universe of discourse, are shown in Fig. 2. Fig. 3 shows the output of the FDA membership functions which are used to evaluate the crisp outputs through the application of fuzzy inference (modus ponens via max-product rule) and center of gravity (COG) defuzzification [10]. The fuzzy relational surfaces for adjusting and associative operation are shown in Fig. 4.

4.2 Results and discussion

The series of simulation studies were performed to compare the PDA, JPDA, and FDA algorithms which shown in Fig. 5. It can be seen that the target I track has been lost (Fig 5a) using PDA. Fig 5b was suggest that the JPDA can track two targets successfully when PDA cannot, but there exist some tracking interference around the targets closely spaced. FDA not only improve the filtering quality but also the trackability. The root mean square error (RMSE) is used to compare tracking performance. It is clearly seen from Fig. 6 that considerable reduction in position errors can be achieved. Next we conducted 20 runs of the three algorithms while increasing clutter density from $2\times10^{-4}$ to $16\times10^{-2}/m\times mrad$. The average RMSE plotted against clutter densities in Fig. 6. The examination of these figures indicates that the fuzzy
approach is not only can converge on the target tracks form light to heavy cluttered environment but also high tracking accuracy. Simulations have revealed that the FDA is much more robust and stable than its counterpart.

\[
\begin{align*}
\text{target I} \\
\text{target II}
\end{align*}
\]

(a) PDA algorithm

\[
\begin{align*}
\text{(b) JPDA algorithm} \\
\text{(C) FDA algorithm}
\end{align*}
\]

(a) Target I

(b) Target II

Fig.6 RMSE of position estimates for different tracking algorithms (clutter density = \(16\times10^{-4}/\text{m*mrad}\)).

5. Conclusions

In this paper, we have presented a set of fuzzy propositions that can be incorporated with the conventional extended Kalman filter for multi-target tracking in a cluttered environment. The simulation examples were given which shows that the proposed approach reduces effectively the maneuvering and cluttered effects. The new FDA approach was based on 49 heuristics. These heuristics are codified to compute the degree to which each measurement within the gate of tracking filter belongs to the true measurement fuzzy set. Our developed filtering algorithm is simple in structure and gives an explicit indication of how to incorporate useful knowledge into the tracking problem.

References


