A New Approach of Data Association Technique

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Abstract

Multiple-target tracking algorithm plays an important role in radar systems. Data association is the most important technique to solve the tracking problems of between measurements and existing tracks. A new approach to tracking algorithm for radar system based on the neural network used Competitive Hopfield Neural Network is investigated. The proposed algorithm will solve both the data association and the target tracking problems simultaneously. Moreover, one simple detection and estimation algorithm denoted adaptive procedure will be applied when tracking targets with maneuvering situations.

Keywords: Data association, Neural network, Adaptive procedure

1. Introduction

Data association technique is the most important technique in multiple-target tracking (MTT) systems. Once the measurement vector received by the radar sensor, such a technique is applied to compute the relation of measurements and each existed target. Therefore, the best estimates for the tracking targets will be obtained. The algorithms of radar estimation system have been investigated in many papers. Fisher and Mayback [1] addressed a multiple adaptive estimation algorithm for the tracking system. Okello and Ristic [2] discussed in the literature point to multiple sensor fusion previous works done in this area. A well-known data association algorithm denoted as the Joint Probabilistic Data Association method which is suited for a high false target density environment was also addressed in [3]. These techniques of data association may be nearest neighbor or all neighbors-based, usually consider the relations between radar measurements and existing targets independently. However, the data association problems should be considered globally. Based on this consideration, this paper proposes a multiple-target tracking approach using a neural network technique to solve the data association problem and to obtain a global matching between radar measurements and each existed target. Chung et al. [4] developed a new approach dented the Competitive Hopfield Neural Network (CHNN) to improve the Hopfield Neural Network wherein a cooperative decision is made based on the simultaneous input of a community of neurons. Each neuron receives information from other neurons and also gives information to other neurons. With this collective information, each neuron settles to a stable stage with the lowest value of a predefined energy function. Based on the CHNN approach, the association between radar measurements and each existing target can be obtained under global optimal considerations which in turn, can increase the accuracy of radar tracking systems.

2. Data Association Algorithm

The dynamic model of tracking system can be defined to be state variable equations which are as follows:

$$X(k+1) = F(k)X(k) + G(k)W(k) \tag{1}$$

$$Y(k) = H(k)X(k) + V(k) \tag{2}$$

In order to solve the tracking problem, a well known algorithm denoted as Kalman filter is applied. In a dense target environment, data association is the most important technique to keep the target in track during the tracking process. Once the radar measurements are obtained, an approach using neural network is applied to obtain the solution of the MTT problems and is described as follows. For each step k, once a measurement vector is received, the corresponding probability for each hypothesis can be obtained from a formula derived as follow. Let

$$Y^k = \{Y(0), Y(1), \ldots\ldots\ldots\ldots, Y(k)\} \tag{3}$$

$$\beta^k = \{\beta(0), \beta(1), \ldots\ldots\ldots\ldots, \beta(k)\} \tag{4}$$

Where $\beta(k)$ is the vector whose entries consist of the uncertain parameters. The probability density function of $Y(k)$ based on β^{k-1} and Y^{k-1} can be computed as follows:

$$p_x^i(Y(k) \mid \beta^{k-1}, Y^{k-1}) = \frac{1}{(2\pi)^{m/2} \mid S(k) \mid^{1/2}} \exp\{-\frac{1}{2}\tau^T(k) S^{-1}(k) \tau(k)\} \tag{5}$$

where m is the dimension of the measurement vector, $\tau(k)$ is the innovation due to $Y(k)$, and $S(k)$ is the innovation covariance matrix. These equations can be obtained from the Kalman filter equations as

$$\tau(k) = Y(k) - \hat{Y}(k) \tag{6}$$

$$S(k) = H(k)P(k \mid k-1)H^T(k) + R(k) \tag{7}$$

For each measurement, we can obtain one weighting probability p_x^i corresponding to the correlated target. Moreover, in order to have clear probability value between each pair of measurement and target, we define

$$P_{x,i} = \frac{p_x^i}{\sum_{v=1}^{n} p_v^i} \tag{8}$$

which is the normalized probability for the *x-th* measurement and the *i-th* target.

In applying the neural network to the data association, we define the way of neuron updating rule and the Lyapunov function of the two-dimensional Hopfield network. Assume that the network consists of n*m mutually interconnected neurons, where $V_{x,i}$ denotes the binary state of the (x,i)-th neuron and $T_{x,I;y,j}$ denotes the interconnection strength between neuron (x,i) and neuron (y,j). A neuron (x,i) in this network receives weighted inputs $T_{x,I;y,j}\ V_{x,i}$ from each neuron (y,j) and a bias input $I_{x,i}$ from outside. Thus, the total input to neuron (x,i) is computed as

$$\mathrm{U}_{x,i} = \sum_{y=1}^{n}\sum_{j=1}^{m} T_{x,i;y,j} V_{y,j} + I_{x,i} \tag{9}$$

Then the state of $V_{x,i}$ is determined by $V_{x,i}$ =1 if U≧0, and 0 if otherwise. This way of neuron updating rule is proven to decrease the Lyapunov function of the two-dimensional Hopfield network given by

$$\mathrm{E} = -\sum_{x=1}^{n}\sum_{y=1}^{n}\sum_{i=1}^{m}\sum_{j=1}^{m} T_{x,i;y,j} V_{x,j} V_{y,j} - 2\sum_{x=1}^{n}\sum_{i=1}^{m} I_{x,i} V_{x,i} \tag{10}$$

In applying the network in data association, let the state of $V_{x,j}$ indicate an association status between the *x-th* radar measurement and the *i-th* target, with "1" and "0" indicating associated and not associated, respectively. Then the objective function used for obtaining measurements and radar targets association with the best decision is given by

$$E = A\sum_{i=1}^{m}\sum_{x=1}^{n}\eta_{x,i}V_{x,i} + B\sum_{x=1}^{n}\sum_{y=1}^{n}\sum_{i=1}^{m}\sum_{j=1}^{m}V_{x,i}V_{y,j}\delta_{x,y} + C\sum_{i=1}^{m}\left(\sum_{x=1}^{n}V_{x,i} - 1\right)^2 \tag{11}$$

where $\eta_{x,i} = \dfrac{1}{P_{x,i}}$

The first term is the sum total of the related parameter between the associated measurements and the radar targets. In data association, it is unavoidable to encounter a situation wherein none of the newly obtained measurements is fit for some specific targets. In this case, the previous target information will be chosen as the next target information. Assume that the m targets are arranged in front of the $n-m$ real measurements to make a total of n measurements. The second term in Eq.(11) attempts to ensure that each measurement can be associated with only one target. The third term forces the condition that each target has one and only one associated measurement. The constants A, B, and C specify the important factors of the three terms. In order to reduce the burden of determining the values of the constant factors, a competitive winner-take-all updating is proposed as follows:

$$V_{x,i} = \begin{cases} 1, & if \quad U_{x,i} = \max\{U_{1,i} \cdots\cdots U_{n,i}\} \\ 0, & otherwise \end{cases}$$

(12)

With this modified updating rule, the hard constraint that each target should be associated with one and only one measurement will be automatically embedded inside the network evolution results. As such, the third term can be naturally removed from the objective function.

Comparing the resultant objective function with the Lyapunov function of the two-dimensional Hopfield network in Eq. (10), we can obtain

$$I_{x,i} = -\frac{A}{2}\eta_{x,i} \tag{13}$$

$$T_{x,i;y,j} = -B\delta_{x,y} \tag{14}$$

3. Maneuvering Estimation and Adaptive Procedure

If the target maneuvering situation is happened, an adaptive procedure which modifies the Kalman filter equations is described as follows. Let

$$\tau(k) = Y(k) - H(k)\hat{X}(k|k-1) \tag{15}$$

$$\beta(k) = H(k)P(k|k-1)H^T(k) \tag{16}$$

$$S(k) = \beta(k) + R(k) \tag{17}$$

where τ (k) is the measurement innovation and S(k) is the innovation covariance matrix.

If the target has a sudden maneuver, then this algorithm will detect this situation based on statistical calculations. In this algorithm, the components which have jumps are first detected using the following test

$$|\tau_i(k)| \le \left|D\sqrt{S_{ii}(k)}\right|, \textit{ for all} \quad i \tag{18}$$

where the subscript i means the i-th component of a vector, and D is a constant related to the Gaussian probability density function. The variance of the rejected innovation can be modified as

$$D^2 = \tau_i^2(k)\{a_i(k)\beta_{ii}(k) + R_{ii}(k)\}^{-1} \tag{19}$$

so that τ (k) exists on the boundaries of the acceptable region defined by Eq. (18). Thus, the parameter $a_i(k)$ can be computed as follows:

$$a_i(k) = \frac{[\tau_{ii}(k)/D]^2 - R_{ii}(k)}{\beta_{ii}(k)} \tag{20}$$

In order to keep the target in track, the covariance of the prediction error P(k|k-1) is modified to [$a_m(k)$ P(k|k-1)], where $a_m(k)$ is the largest value of all the $a_i(k)$. With this approach, the Kalman gain is increased and as such, the tracking filter will have faster responses for the sudden maneuvering situations. Therefore, a better performance will be obtained.

4. Simulations

The results of tracking multiple targets in the planar case were simulated under several different situations. First, the approach is tested in the case of five targets and fifteen measurements as shown in Figure 1. The situation before calculating the data association logic is shown in Figure 1(a). Figure 1(b) shows the situation after calculating the data association logic wherein five optimal associations between the targets and the measurements are selected.

A simulation with maneuvering conditions is also presented. Table 1 shows the target initial conditions for the simulation example which tracks three targets with maneuvering situations shown in Table 2. We apply two different data association techniques namely, the one-step conditional maximum likelihood and the proposed algorithm in this paper for comparison. The simulation result of tracking three maneuvering targets is shown in Figure 2. The simulation results of corresponding average RMS errors are shown in Tables 3 and 4, respectively. According to the simulation results, we know that the performance of the proposed algorithm is quite well.

5. Conclusions

A new data association algorithm based on a Competitive Hopfield Neural Network for tracking multiple targets was accomplished in this paper. This tracking technique has the advantage of choosing the optimal correlation between radar measurements and existing target tracks. Furthermore, we also applied the multiple target tracking procedure for tracking targets. Based on the simulation results, this algorithm was capable of obtaining the optimal correlations between existed targets and radar measurements. It performed quite well also when tracking various situations' targets.

6. Reference

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Table 1. Initial conditions of Three Targets

	$x(m)$	$\dot{x}(m/s)$	$y(m)$	$\dot{y}(m/s)$
Target1	1800	450	10000	10
Target2	2000	450	16000	10
Target3	2100	450	40000	10

Table 2. Target acceleration conditions of three targets

Step	20~30 step		50~60 step		other step	
Acceleration	a(x) (m/s^2)	a(y) (m/s^2)	a(x) (m/s^2)	a(y) (m/s^2)	a(x) (m/s^2)	a(y) (m/s^2)
Target1	25	25	15	-25	0	0
Target2	15	25	25	-5	0	0
Target3	25	-25	15	25	0	0

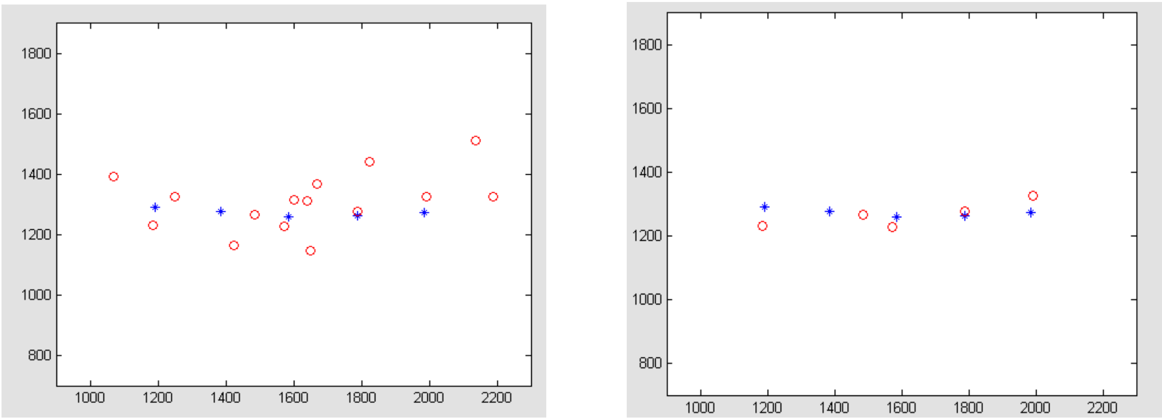
Table 3. Simulation Results of Tracking Three Targets Using One-step conditional Maximum Likelihood

	Target1	Target2	Target3
Position errors	168.18	169.62	170.11
Velocity errors	42.56	41.23	41.18

Table 4. Simulation Results of Tracking Three Targets Using the Proposed Algorithm

	Target1	Target2	Target3
Position errors	153.21	150.32	155.36

Velocity errors	33.50	34.15	35.23



(a) (b)

Figure 1. Data association result for tracking five targets in one step (* true targets , º radar measurements)

(a) Before calculating the data association algorithm

(b) After calculating the data association algorithm

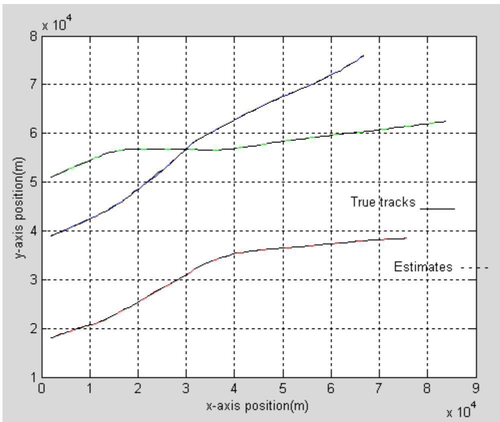


Figure 2. Simulation of Tracking Three Targets