The Dual-Kalman Filtering and Neural Solutions to Maneuvering Estimation Problems*

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Tracking maneuvering targets in a radar system is more complicated because the target accelerations cannot be directly measured. It may occur severe tracking error even diverge the estimates when the maneuvering situations are happened. In this paper, we develop a Dual-Kalman filtering algorithm to handle the maneuvering targets' tracking problems. In this approach, two collaborative Kalman filters are devised which one for pursuing the track estimation and the other for estimating the status of maneuver. Based on this approach, the most approximate target's acceleration can be detected and estimated in real time. Moreover, it is also shown that one Competitive Hopfield Neural Network-based data association combined with a multiple-target tracking system demonstrates target tracking capability.

Keywords: maneuvering targets, Dual-Kalman filtering algorithm, competitive hopfield neural network, data association, multiple-target tracking system

1. INTRODUCTION

Multiple-target tracking (MTT) is an essential requirement for radar surveillance systems [1]. In real applications of MTT, both maneuvering and non-maneuvering targets must be tracked simultaneously. When maneuvering situations are occurred, the track estimates are easily distorted or divergent. If the targets with maneuvering situations, it will be more complicated because the radar system can not directly measure target accelerations. In tracking procedure, how to detect and estimate the maneuvering status effectively is very important.

The related techniques of tracking multiple maneuvering targets have been addressed in several papers. For example, an acceleration estimation algorithm based on the range rate measurement was developed in [2]. The interacting multiple model (IMM) together with the JPDA methods [3] in target tracking applied two or more maneuver modes where the modes will be changed during tracking procedure according to target

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situations. An adaptive procedure for multiple maneuvering target tracking was applied by [4, 8]. In a dense target environment, the data association algorithm is the key technique that is applied to associate measurements with the predicted targets and its related techniques have been addressed by some papers. For example, the data association algorithm referred to as Joint Probabilistic Data Association (JPDA) method [5, 6] suited for a high false target density environment. Another method named a unifying approach to MTT which was developed in [6]. An approach using neural networks denoted Competitive Hopfield Neural Network (CHNN)-based data association algorithm for radar multiple target tracking is also proposed in [8].

Although radar tracking problems have been investigated by many authors for a long time, they still remain a great deal of debate surrounding these problems. In this paper, we propose a Dual-Kalman filtering based algorithm to handle the maneuvering targets. In this approach, two collaborative Kalman filters are devised which one for pursuing the track estimation and the other for estimating the status of maneuver. The algorithm will combine the tracking models estimates to obtain the final estimate. Moreover, we also apply the CHNN-based data association algorithm to our multiple-target tracking system. Base on this approach, we can solve the maneuvering and data association problems simultaneously.

The rest of the paper is organized as follows. The mathematic models of tracking system are presented in section 2. Moreover, the data association technique based on the Competitive Hopfield Neural Network is also described in this section. In order to track the maneuvering targets effectively, an improved approach denoted the Dual-Kalman filtering algorithm to handle maneuvering problems is developed in section 3. The simulation results of the multiple-target tracking are presented in section 4. Finally, the conclusion of this paper is drawn in section 5.

2. MATHEMATIC MODELS AND DATA ASSOCIATION TECHNIQUE

In this section, the mathematic models for a multiple-target tracking algorithm are defined as follows.

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

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

$X(k)$: the target state vector
$Y(k)$: the measurement vector
$F(k)$: the state transition matrix
$G(k)$: the gain matrix of the target
$U(k)$: the forcing input vector
$H(k)$: the measurement matrix
$V(k)$: the system noise associated with the target, assumed to be normally distributed with zero mean and variance $Q(k)$
$W(k)$: the measurement noise associated with the target, assumed to be normally distributed with zero mean and variance $R(k)$, and uncorrelated with $V(k)$

In MTT, data association algorithm is the key technique to compute the correlations between measurements and existing targets. In this paper, the Competitive Hopfield Neural Network-based algorithm [8] is applied to the potential-target measurements to obtain the solution of the data association problems. In applying the network to data association, let the state of $V_{x,i}$ denote an association status between the xth radar measurement and the ith 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

$$E = A\sum_{x=1}^{n}\sum_{i=1}^{m} d_{x,i}V_{x,i} + B\sum_{x=1}^{n}\sum_{y=1}^{n}\sum_{i=1}^{m}\sum_{j=1}^{m} V_{x,i}V_{y,j}\delta_{x,y} + C\sum_{i=1}^{m}\left(\sum_{x=1}^{n} V_{x,i} - 1\right)^2. \tag{3}$$

The distance $d_{x,i}$ is then defined as

$$d_{x,i} = \begin{cases} \left[\tau^T(k)S(k)^{-1}\tau(k)\right]^{1/2} & \text{if } x \neq i \text{ and } x > m \\ \infty & \text{if } x \neq i \text{ and } 1 \leq x \leq m, \\ r & \text{if } x = i \end{cases} \tag{4}$$

where $\tau(k) = Y(k) - H(k)\hat{X}(k \mid k-1)$, and $S(k)$ is the covariance matrix of the innovation, and r is the radius of gate.

The second term in Eq. (3) 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 parameters A, B, and C specify the important factors in the object function. In order to reduce the burden of determining the values of the weighting factors, a competitive winner-take-all updating is proposed as follows:

$$V_{x,i} = \begin{cases} 1, & \text{if } U_{x,i} = \max\{U_{1,i}, \ldots, U_{n,i}\} \\ 0, & \text{otherwise} \end{cases}. \tag{5}$$

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 subsequently removed from the objective function. Thus, the objective function can be further simplified as follows:

$$E = A\sum_{x=1}^{n}\sum_{i=1}^{m} d_{x,i}V_{x,i} + B\sum_{x=1}^{n}\sum_{y=1}^{n}\sum_{i=1}^{m}\sum_{j=1}^{m} V_{x,i}V_{y,j}\delta_{x,y}. \tag{6}$$

It is also worth noting that once the competitive winner-take-all updating is applied, with A set to be 1, B can be easily set to be greater than the radius of gate, r, a relatively constant value. By so doing the network would be avoided from trapping into irrational solutions.

Comparing the resultant objective function with the Lyapunov function of the twodimensional Hopfield network in Eq. (3), we can obtain

$$I_{x,i} = -\frac{A}{2} d_{x,i}, \tag{7}$$

$$T_{x,i;y,j} = -B\delta_{x,y}. \tag{8}$$

3. MANEUVERING DETECTION AND DUAL-KALMAN FILTERING ALGORITHM

If the target initiates and sustains a sudden maneuver, the system should detect and estimate the situation quickly and correctly. An algorithm denoted Dual-Kalman filtering algorithm is applied in this paper. Based on this approach, the most approximate target's acceleration will be estimated in real time. Apply such estimation results to our tracking algorithm and then the better tracking performance will be obtained. This algorithm is derived as follows. In order to estimate the status of maneuvering, the dynamic systems are defined as follows.

System model

$$X(k+1) = F(k)X(k) + G(k)U(k) + V(k), \tag{9}$$

$$X_a(k+1) = F(k)X(k) + G(k)U_a(k) + V(k). \tag{10}$$

Measurement model

$$Y(k) = H(k)X(k) + W(k), \tag{11}$$

$$Y_a(k) = H(k)X_a(k) + W(k). \tag{12}$$

Two estimation models are defined in the tracking system. The $U(k)$ is the real acceleration of targets and the $U_a(k)$ is the assumed acceleration. Base on the following algorithm, the maneuvering status will be estimated. Let

$$\hat{X}(k \mid k-1) = E[X(k) \mid Y^{k-1}, \{U(k)\}] \tag{13}$$

$$\hat{X}_a(k \mid k-1) = E[X(k) \mid Y^{k-1}, \{U_a(k)\}] \tag{14}$$

$$B(k) = \hat{X}_a(k \mid k-1) - \hat{X}(k \mid k-1) \tag{15}$$

$$\Delta U(k) = U_a(k) - U(k). \tag{16}$$

Based on the Kalman filter equations, the estimation error can be obtained.

$$\begin{aligned} B(k+1) &= \hat{X}_a(k+1 \mid k) - \hat{X}(k+1 \mid k) \\ &= F(k)\hat{X}_a(k \mid k) + G(k)U_a(k) - F(k)\hat{X}(k \mid k) - G(k)U(k) \\ &= F(k)[I - K(k)H(k)]B(k) + G(k)\Delta U(k). \end{aligned} \tag{17}$$

Assume that

$$B(k) = D(k)\Delta U(k) \text{ and } D(0) = 0. \tag{18}$$

Therefore,

$$D(k+1) = F(k)[I - K(k)H(k)]D(k) + G(k). \tag{19}$$

Based on Kalman filter, the measurement innovation can be obtained.

$$\tilde{Z}(k) = H(k)X(k) - H(k)\hat{X}(k \mid k-1) \tag{20}$$

$$\tilde{Z}_a(k) = H(k)X(k) - H(k)\hat{X}_a(k \mid k-1) \tag{21}$$

$$\tilde{Z}_a(k) - \tilde{Z}(k) = H(k)\hat{X}_a(k \mid k-1) - H(k)\hat{X}(k \mid k-1) = H(k)D(k)\Delta U(k). \tag{22}$$

And then

$$\tilde{Z}_a(k) = \tilde{Z}(k) + H(k)D(k)\Delta U(k). \tag{23}$$

Eq. (23) is the observation model of $\Delta U(k)$. In the system, we suppose all noises are Gaussian, therefore, the measurement innovation is considered as Gaussian quantity. Based on this assumption, the acceleration status estimation algorithm can be modeled as:

State model

$$\Delta U(k+1) = \Delta U(k). \tag{24}$$

Measurement model

$$\tilde{Z}_a(k) = H(k)D(k)\Delta U(k) + \tilde{Z}(k). \tag{25}$$

The covariance matrix of estimation error is

$$P_a(k \mid k) = E\{[\Delta U(k) - \Delta\hat{U}(k \mid k)][\Delta U(k) - \Delta\hat{U}(k \mid k)]^T\}. \tag{26}$$

Assume

$$\Delta\tilde{U}(k+1 \mid k) = \Delta U(k+1) - \Delta\hat{U}(k+1 \mid k) \tag{27}$$

$$P_a(k+1 \mid k) = E[\Delta\tilde{U}(k+1 \mid k)\Delta\tilde{U}^T(k+1 \mid k)] = P_a(k \mid k) \tag{28}$$

$$\hat{\tilde{Z}}(k+1 \mid k) = H(k+1)D(k+1)\Delta\hat{U}(k+1 \mid k) \tag{29}$$

$$\begin{aligned} S_a(k+1) &= \operatorname{cov}[\tilde{Z}_a(k+1 \mid k)] \\ &= [H(k+1)D(k+1)]P_a(k+1 \mid k)[H(k+1)D(k+1)]^T + R_a(k+1) \end{aligned} \tag{30}$$

$$K_a(k+1) = P_a(k+1|k)(H(k+1)D(k+1))^T S_a^{-1}(k+1) \tag{31}$$

$$\Delta\hat{U}(k+1|k+1) = \Delta\hat{U}(k+1|k) + K_a(k+1)[\tilde{Z}_a(k+1) - H(k+1)\Delta\hat{U}(k+1|k)] \tag{32}$$

Finally, the updated covariance matrix of estimation error is

$$P_a(k+1|k+1) = P_a(k+1|k) - K_a(k+1)S_a(k+1)K_a^T(k+1). \tag{33}$$

If the target moves in constant speed, the system will choose the first model which is defined as

$$X(k + 1) = F(k)X(k) + V(k), \tag{34}$$

$$Y(k + 1) = H(k)X(k + 1) + W(k + 1). \tag{35}$$

The tracking procedure is based on the general Kalman filter equations. However, if the target maneuvering situations are happened, the system will choose the second model which is defined as

$$X(k + 1) = F(k)X(k) + D(k)\Delta U(k) + V(k), \tag{36}$$

$$Y(k + 1) = H(k)X(k + 1) + W(k + 1). \tag{37}$$

4. SIMULATIONS

In order to evaluate the performance of the proposed algorithm, a simulation program is developed. In our simulations, the measurement noise and clutter points were created using random number generators. The measurement data were obtained using the true target motion in addition to the measurement errors. The clutter points were assumed to be uniformly located in the measurement space with an average of about two clutter points per validation gate. The results of tracking multiple targets in the planar case were simulated under several different situations.

Two kinds of simulation examples were conducted. In the simulations, all the targets were chosen with the initial conditions as listed in Table 1. The maneuvering situations for all targets were shown in Table 2. The standard deviation of system position noise was 20 m for both X and Y axis. The standard deviation of measurement position noise was assumed to be 200 m. Moreover, the standard deviation of the velocity noise was at least 0.05 times the mean velocity. We assumed all the noise to be uncorrelated. In the simulation, we applied three different kinds of approaches which were the general estimation filter, adaptive procedure [8], and the Dual-Kalman filtering algorithm for comparison. The CHNN-based data association algorithm [8] was used in all simulations. The values A = 1 and B = r + 1, where r is the radius of the gate. The number of returns for each step was assumed to be five times of the number of targets. In other words, all conditions were the same in all simulation examples. The simulation results of tracking two maneuvering targets are shown in Figs. 1 to 3, respectively. After fifty Monte-Carlo runs, their tracking RMS errors of positions and velocities are shown in Tables 3 to 5, respect-

Table 1. Initial condition for simulation examples.

	$x(m)$	$\dot{x}(m/s)$	$y(m)$	$\dot{y}(m/s)$
Target 1	100	230	5000	50
Target 2	100	130	4500	100
Target 3	100	150	4000	150
Target 4	100	270	3500	200

Table 2. Target acceleration situations.

Step	10-20 step		25-35 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)
	50	– 30	– 50	30	0	0

Table 3. Simulation results of tracking two targets using general filter algorithm.

	Position errors	Velocity errors
Target 1	180.2	40.1
Target 2	176.8	43.2

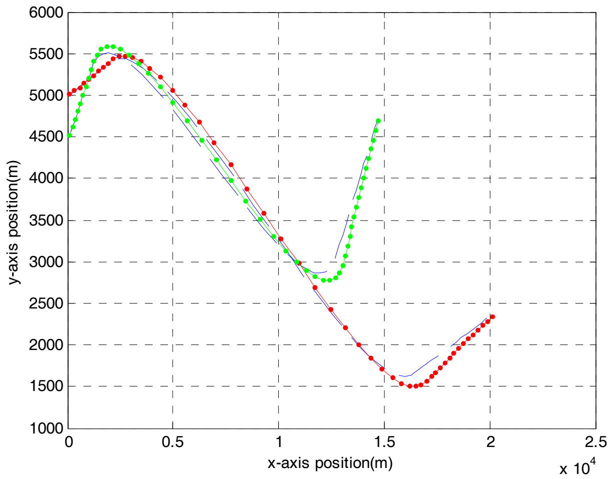

Fig. 1. Track two targets using general filter algorithm.

tively. The simulation results of tracking four maneuvering targets are shown in Figs. 4 to 6, respectively. The tracking RMS errors of positions and velocities are shown in Tables 6 to 8, respectively. By comparing the results in Tables 3 to 8, we can see that the adopted maneuvering approach, Dual-Kalman filtering algorithm, shows smaller averaged position errors and velocity errors than the other two algorithms for all targets. According to the simulation results, we can see that the proposed algorithm demonstrates better performance, and capable of tracking multiple targets in various situations.

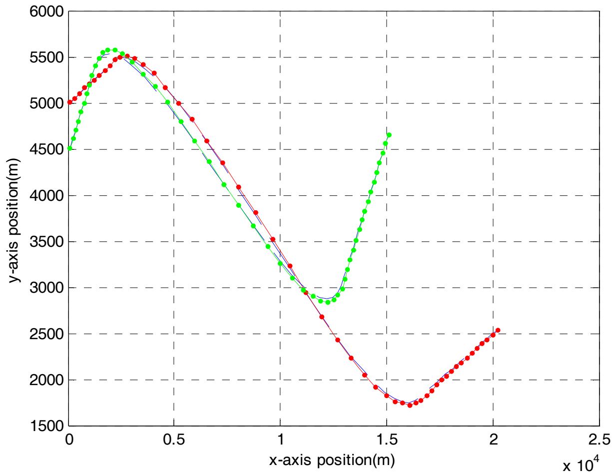

Fig. 2. Track two targets using adaptive procedure algorithm.

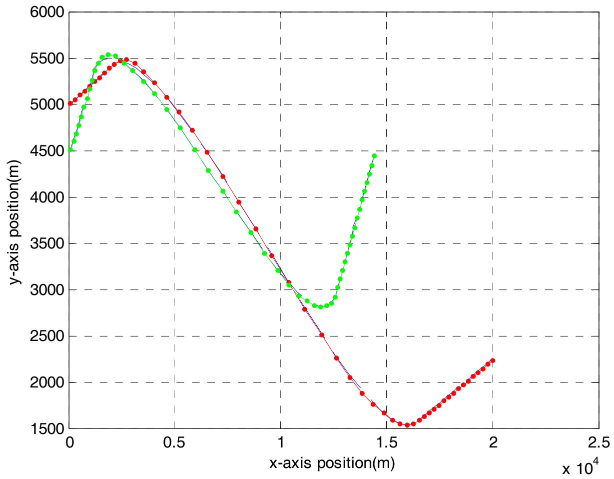

Fig. 3. Track two targets using Dual-Kalman filter algorithm.

Table 4. Simulation results of tracking two targets using adaptive procedure algorithm.

	Position errors	Velocity errors
Target 1	131.3	30.1
Target 2	129.8	29.2

Table 5. Simulation results of tracking two targets using Dual-Kalman filter algorithm.

	Position errors	Velocity errors
Target 1	121.3	27.1
Target 2	117.8	26.2

Table 6. Simulation results of tracking four targets using general filter algorithm.

	Position errors	Velocity errors
Target 1	182.3	41.1
Target 2	174.2	44.6
Target 3	178.9	43.2
Target 4	176.3	39.2

Table 7. Simulation results of tracking four targets using adaptive procedure algorithm.

	Position errors	Velocity errors
Target 1	132.3	30.3
Target 2	131.8	29.8
Target 3	135.3	29.6
Target 4	133.6	30.3

Table 8. Simulation results of tracking four targets using Dual-Kalman filtering algorithm.

	Position errors	Velocity errors
Target 1	122.3	26.1
Target 2	118.2	26.9
Target 3	118.6	25.7
Target 4	117.3	26.8

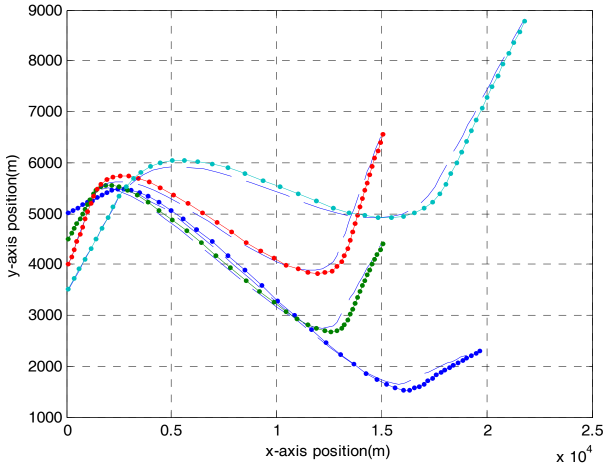

Fig. 4. Track four targets using general filter algorithm.

5. CONCLUSION

A Dual-Kalman filtering algorithm for tracking multiple maneuvering targets has been accomplished in this paper. Based on this approach, the maneuvering status can be-detected and estimated in real time. This algorithm consists of a CHNN-based data asso-

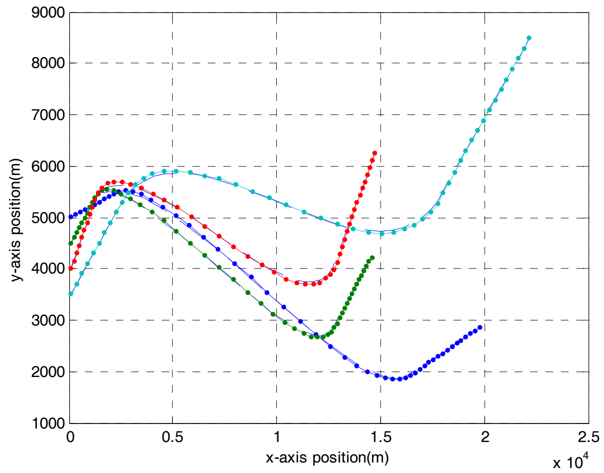

Fig. 5. Track four targets using adaptive procedure algorithm.

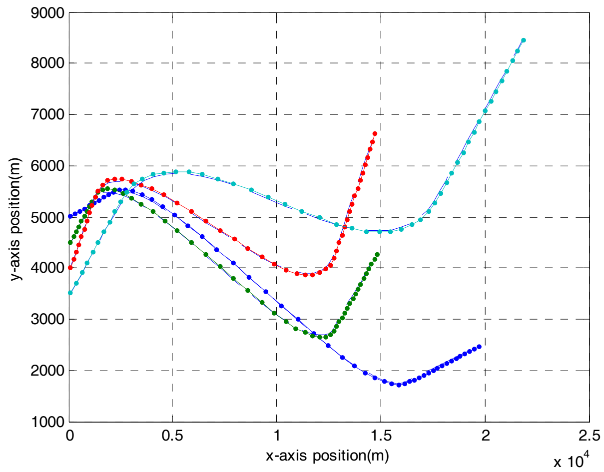

Fig. 6. Track four targets using Dual-Kalman filter algorithm.

ciation technique and a Dual-Kalman filtering algorithm. The advantage of this tracking technique is that it is a relatively simple recursive method which can be used to solve multiple maneuvering and data association problems simultaneously. According to the simulation results, this algorithm is capable of tracking multiple targets in various situations and has good performance.

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