Radar Maneuvering Target Tracking System Using Multi-model Algorithm

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Abstract

The tracking system for multiple maneuvering targets using a multi-model algorithm has been developed in this paper. This system is implemented with an adaptive filter which consists of a data association technique and a multiple model algorithm as an adaptive maneuvering compensator. The advantage of this approach is that it can adjust the estimation depending on various targets' situations. Via this approach, both data association and target maneuvering problems can be solved simultaneously. According to the simulation results, we convince that this approach can track multiple maneuvering targets underlying various situations.

Keywords: Multiple maneuvering targets, Adaptive filter, Kalman filter

1. Introduction

Multiple-target tracking (MTT) is an important algorithm in the radar surveillance systems. When target tracks are confirmed, the quantified information of targets, such as the target position and velocity, can be estimated for each track. Generally, MTT tracking problems consist of three parts: track initiation, track maintenance, and track deletion. The major problem of a tracking algorithm in a multiple-target environment is data association and maneuvering compensation. Such a data association technique that is applied to associate measurements with the predicted targets is the key development in MTT. A data association algorithm, referred to as Joint Probabilistic Data Association (JPDA) method suited for a high false target density environment [1]. Some other radar tracking algorithms were also discussed in several other papers [5,6]. Another approach using neural networks to multiple target tracking are also proposed in [7]. In a dense target environment, some targets can be very close to each other. An effective approach to solving data association problem should be considered globally. Based on this consideration, this paper proposes a suitable multiple-target tracking data approach guaranteed to provide a proper solution to data association.

Moreover, another problem of MTT algorithm is that the track estimates are easily distorted or even divergent because of the target-maneuvering situation. Although it has been investigated by many authors, such as [2-4], for a long time, there still remains a great deal of debate surrounding this problem. This problem is much more complicated in a multi-target environment, which needs a technique that considers the performance of data association together with maneuver detection and estimation. One improved tracking algorithm for multiple maneuvering targets is developed in this paper. The fundamental concept underlying this approach is to design a multiple model estimator together with an adaptive algorithm for each target situations and to pursue the best estimation for true targets. Base on this approach we can solve the problems of data association and target maneuvering simultaneously.

2. System Model Definitions

In this section, a dynamic model for a multi-target tracking algorithm is defined as:

$$\begin{aligned} X(k+1) &= F(k)X(k)+G(k)W(k) \\ Y(k) &= h(X(k))+V(k) \end{aligned} \quad (1)$$

where

X(k) : the state vector of the target

Y(k) : the measurement vector of the target

W(k): the system noise associated with the target, assumed to be normally distributed with zero mean and variance *Q(k)*

V(k): the measurement error associated with the target , assumed to be normally distributed with zero mean and variance *R(k)*, and uncorrelated with *W(k)*

h(X(k)): the transformation from Cartesian coordinates to polar coordinates corresponding to the target

F(k) : the transition matrix of the target

G(k): the noise gain matrix of the target

The vector h is the transformation from Cartesian coordinates to the polar coordinates defined as

$$r(k) = \sqrt{x^2 + y^2} \quad (2)$$

$$\dot{r}(k) = \frac{\dot{x}x + \dot{y}y}{r} \quad (3)$$

$$\theta(k) = \arctan(y/x) \quad (4)$$

where r , $\dot{r}$, and θ denote the target range, range rate , and azimuth angles , respectively . The noisy radar measurements of range, range rate, and azimuth angles for the target are denoted by $Y(k)$, where

$$Y(k) = [r(k)\ \dot{r}(k)\ \theta(\mathrm{k})]^{\mathrm{T}}$$

The covariance matrices of system noise *Q* and measurement error for the target Rare assumed to be

$$Q = diag[\sigma_x^2\ \sigma_{\mathrm{y}}^2]$$

$$R = diag[\sigma_r^2\ \sigma_{\dot{r}}^2\ \sigma_\theta^2].$$

3. Data Association Algorithm

A suboptimal approach denoted 1-step Conditional Maximum Likelihood is applied to obtain the solution of the MTT problems and are described as follows. For each step k, once a measurement vector is received, the corresponding likelihood denoted as a weighting coefficient for each hypothesis can be obtained from one formula derived as follows:

Let

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

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

where $\beta(k)$ is the vector whose entries consist of the uncertain parameters. Assuming that β^{k-1} is correctly identified and $V(k)$, $W(k)$ are Gaussian, the conditional probability density function of $Y(k)$ based on β^{k-1} ， Y^{k-1} is

$$\begin{aligned} &p(Y(k)\,|\,\beta^{k-1}, Y^{k-1}) \\ &= \frac{1}{(2\pi)^{m/2}|S(k)|^{1/2}} \exp\{-\tfrac{1}{2}\tau^T(k)S^{-1}(k)\tau(k)\} \end{aligned} \quad (5)$$

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 quantities can be obtained from the extended Kalman filter equations as

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

$$S(k) = H(k)P(k\,|\,k-1)H^T(k) + R(k) \quad (7)$$

where

$$\hat{Y}(k) = h(\hat{X}(k\,|\,k-1) \quad (8)$$

$$H(k) = \left[\frac{\partial h(X(k))}{\partial X(k)}\right]_{X(k)=\hat{X}(k|k-1)} \quad (9)$$

and $P(k\,|\,k-1)$ is the covariance of prediction errors. The suboptimal estimate can be computed, with weights given by the corresponding likelihood functions, from

$$\hat{X}(k|k) = \sum_j p(Y(k)|\beta_{k_j}(k), \beta^{k-1}, Y^{k-1}) \cdot \hat{X}(k|k, \beta_{k_j}(k)) \quad (10)$$

The best 1-step conditional maximum likelihood at step k, based on Y^k, is obtained as the value of $\beta(k)$ which maximizes Equation (5).

4. Adaptive Procedure

If target maneuvers occur, the maneuver detection algorithm and an adaptive feature can modify the parameters of the tracking filter to allow the maneuvers to be tracked without diverging or severely distorting the estimate. Such an adaptive procedure which modifies the extended Kalman filter equations is described as follows. Let

$$\tau(k) = Y(k) - h(\hat{X}(k|k-1)) \quad (11)$$

$$\delta(k) = H(k)P(k|k-1)H^T(k) \quad (12)$$

$$S(k) = \delta(k) + R(k) \quad (13)$$

where $\tau(k)$ is the measurement innovation and S(k) is the innovation covariance matrix. One detection criterion is defined as

$$f(k) = \sum_{j=k-N+1}^{k} \tau^T(j) S^{-1}(j) \tau(j) \underset{H_o}{\overset{H_1}{>}} \varepsilon \quad (14)$$

where H_0 is the hypothesis that system behavior is normal, and H_1 is the hypothesis that the target is moving with maneuvers. Since the noises, $V(k)$ and $W(k)$, have been assumed to be zero mean Gaussian white noise, $f(k)$ is a Chi-squared random variable with $N \cdot m$ degrees of freedom, where N is the residua1 window size and m is the dimension of the measurement vector. The criterion ε can be chosen from standard Chi-squared tables.

After the target maneuvers are detected, one compensation algorithm is applied. The fundamental concept underlying this approach is taking into account of possible maneuver hypotheses for the tracking algorithm. For each of them, the corresponding state estimator is derived based on the Kalman filtering technique. Such a scheme consists of a bank of Kalman filters which will estimate the target's acceleration if the situation of maneuvering is happened. The adaptive algorithm whose flow diagram is shown in Figure 1. Based on this approach, the most approximate target's acceleration will be estimated immediately. Apply such estimation results to our tracking algorithm and a better tracking performance will be obtained.

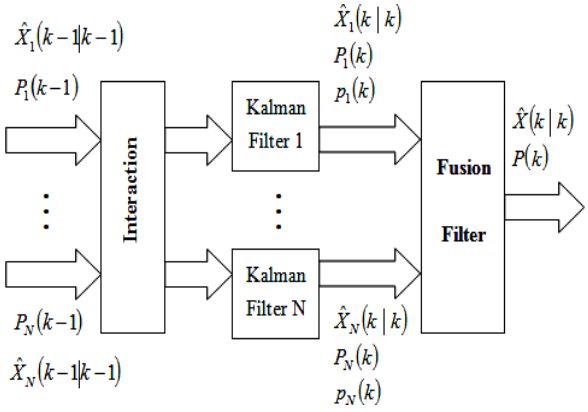

Figure 1. Extended multiple model estimators for tracking maneuvering targets

5. Simulations

The simulation algorithm for the proposed multi-target tracking algorithm is developed. In the simulation, the measurement noise and clutter points were created using random number generators. The measurement data was obtained via a discredited version of true target motion in addition to measurement errors. New measurements that include new targets and false detections were randomly generated based on a uniform distribution function. For the nonlinear measurement model, extended Kalman filters are used to estimate the state vector $\hat{X}(k|k)$ recursively. Once measurement data is received, the corresponding likelihood is calculated based on each hypothesis. The conditional estimate of target states is evaluated and combined with the individual estimate upon each hypothesis, weighted by the corresponding likelihood function.

In order to compare the performance of different algorithm, we simulated each situation by two different approaches.

Method1: Using a general tracking algorithm together with a data association technique

Method2: Using an adaptive tracking algorithm proposed in this paper together with a data association technique

The initial conditions and maneuvering situations of the simulations of tracking four

targets are shown in Table 1 and Table 2, respectively. The simulation results are shown in Figures 2 and 3, and their average tracking errors are shown in Tables 3 and 4. According to the simulation results, the proposed tracking algorithm in this paper works quite well.

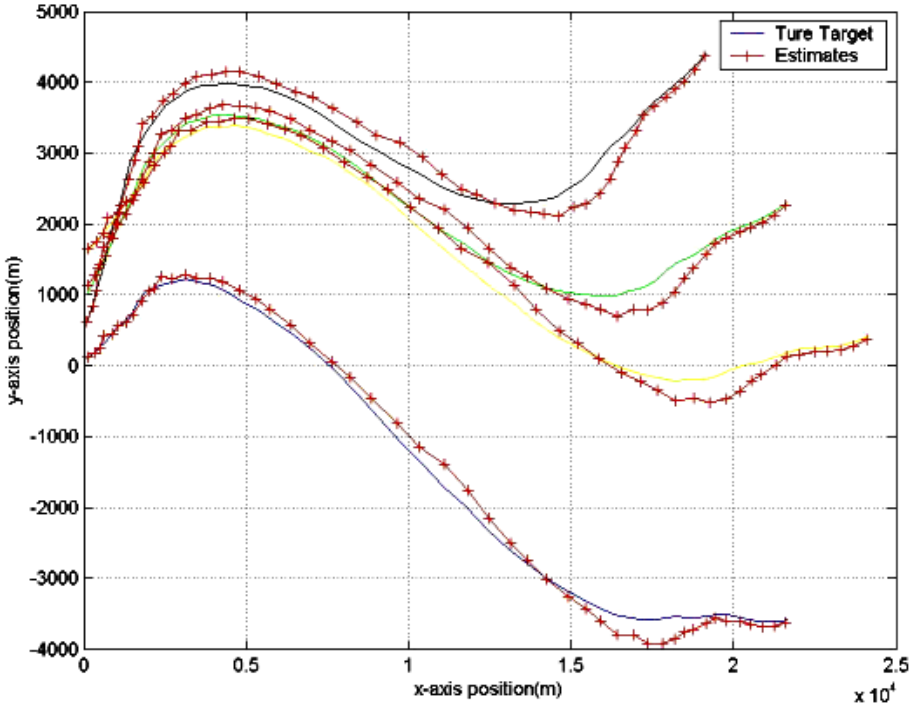

Figure 2. Tracking four targets using general tracking filter

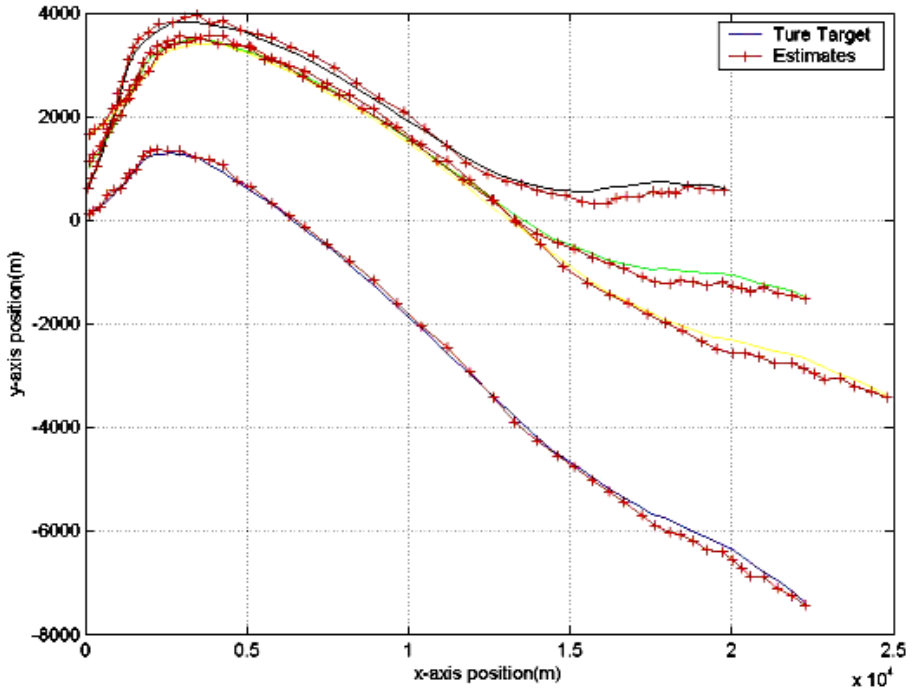

Figure 3. Tracking four targets using extended multiple model estimators

Table 1. Initial conditions for simulation examples

	$x(m)$	$\dot{x}(m/s)$	$y(m)$	$\dot{y}(m/s)$
Target1	100	200	100	100
Target2	100	150	600	250
Target3	100	200	1000	200
Target4	100	250	1600	150

Table 2. Target acceleration situations

Step	10~30 step		35~45 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)
	30	-30	-30	30	0	0

Table 3. Simulation results of tracking four targets using general tracking filter

	Position errors	Velocity errors
Target1	160.2	43.1
Target2	158.1	41.9
Target3	159.6	42.3
Target4	158.5	41.3

Table 4. Simulation results of tracking four targets using extended multiple model estimators

	Position errors	Velocity errors
Target1	145.3	33.7
Target2	142.6	33.2
Target3	140.3	33.8
Target4	143.7	32.3

6. Conclusion

An improved algorithm for tracking multiple maneuvering targets was accomplished in this paper. This algorithm is implemented with an adaptive filter consisting of a data association technique and a bank of Kalman filters. The advantage of this tracking technique is that it is a relatively simple recursive method which can be used to solve multiple maneuvering tracking problems. Via this approach, the maneuvering problems can be solved and it has better performance also. According to the simulation procedure conducted in this paper, it shows that this algorithm was capable of tracking multiple targets in various situations.

7. Acknowledgement

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8. Reference

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