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The Research of Applying A Multi-Observation System to Radar Tracking Algorithm

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Abstract

In view of the lack dynamicity in a tradeficral fiord sensor system, an algorithm of tracking multiple maneuvering targets in a dynamic sensor system is proposed in this paper. The algorithm combines coordinate longer and a multiple sensor data fusion for it to work in the dynamic With the developed algorithm, the sensors can be installed in fixed or moving systems which will improve the tracking accuracy and reliability of radar surveillance. Moreover, in order to solve the data association and target maneuvering situations, a computation logic including gating 1-step conditional maximum likelihood and a variable structure model as an adaptive maneuvering compensator is applied to solve both data association and target maneuvering problems simultaneously. In order to verify this approach, simulations of multi-target tracking problems are conducted. Computer simulation results indicate that this approach successfully tracks multiple targets in a dynamic sensor system and has good performance.

Keywords: dynamic sensor system, multiple sensor data fusion, gating, 1-step conditional maximum likelihood, adaptive maneuvering compensator.

1. Introduction

Multiple-target tracking (MTT) is an essential requirement for radar surveillance systems employing one or more sensors, together with computer subsystems. The objective of the tracking algorithm is to partition the sensor data into sets of observations produced by the same target. Once tracks are formed and confirmed, the number of targets can be estimated and quantities, such as the target position and velocity, can be computed for each track. Generally, MTT tracking problem consists of three parts: track initiation, track maintenance and track deletion. In real applications of MTT, both maneuvering and non-maneuvering targets must be tracked simultaneously.

Several algorithms that have been discussed in the literature point to the past work in this area. An approach of finding a way to incorporate measurements into existing tracks was developed within the framework of Kalman filtering. They make decisions to accept or reject trajectories and then estimate the state conditioned upon the correctness of these decisions. Moreover, Chang and Tabaczynski presented a survey of problems and solutions which deal with target tracking. A well known data association algorithm denoted the joint probabilistic data association (JPDA) method that is suited to a high false target density environment was addressed in [1]. The ordinary PDA tracker performs poorly while tracking crossing targets or when the targets are close to each other. This difficulty is alleviated by the joint probabilistic data association (JPDA) algorithm from the joint likelihood functions corresponding to the joint hypotheses associating all the returns to different permutations of targets and clutter points [1]. A unifying approach to MTT was developed by Emre and Seo [5].

Another difficulty associated with is that the track estimates are easily distorted or divergent because of the target-maneuvering problem. This problem needs a technique that considers the performance of data association together with maneuver detection and estimation. Literatures on this subject can be found in [2-4].

Currently the radar surveillance is usually accomplished by fixed radar systems [6-11]. With this approach when the targets are in occluding conditions, it is unavoidable of miss detection. Furthermore, this fixed radar systems are lack of dynamicity when the enemy could easily destroy them to fail the radar surveillance. Based on these considerations, this paper develops dynamic sensors based multiple targets tracking system, which uses sensors installed in surveillance airplanes for improving the accuracy and reliability of radar surveillance system. In order to provide consistent coordinates in this dynamic sensors based multiple targets tracking system, the ground base station is employed as the coordinate center and the coordinates conversion in the dynamic multiple sensors is performed. Under this consistent coordinates, association between radar measurements and true targets are identified followed by the multiple target tracking procedure. The fundamental concept underlying this tracking algorithm is to define a model for target situations to pursue a correct association between radar measurements and true targets using the 1-step conditional maximum likelihood technique, and to apply an adaptive algorithm for target maneuvering problems. A multiple sensor fusion tracking algorithm is also developed.

2. System Model Definitions

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

$$X(k+1) = FX(k) + GW(k) \tag{1}$$

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

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 normallydistributed with zero mean and variance $Q(k)$

$V(k)$: the measurement error associated with the target , assumed to benormally distributed with zero mean and variance $R_i(k)$, and uncorrelated with $W(k)$.

H_i : the measurement matrix of the target

F : the transition matrix of the target

G : input gain matrix of the target

3. Conversion of the coordinates

In order to organize the local sensor system coordinates, there is a conversion algorithm for central computation system. We assume that the local sensors are built in different airplanes who try to track a missile as shown in Figure1, and the ground radar system is the central sensor system. For the sake of convenient analysis, we use one sensor's data to calculate the relation of the conversion. Then we can expand it to all the sensors in the system, and Figure2 is the concept diagram. Let $T_1 = (x_1, y_1, z_1)$ be the position of the missile with respect to the sensor in the airplane, and T_2 be the position of missile with respect to ground central processor. R_1 and R_2 are the positions of the sensor and central processor with respect to a defined earth coordinate. ΔR is the position the airplane with respect to the central processor. If we let S_1 and S_2 denote the magnitude of T_1 and T_2, then we can have

$$s_1 = |T_1| = \left(x_1^2 + y_1^2 + z_1^2\right)^{1/2} \tag{5}$$

and $$s_2 = |T_2| = |\Delta R + T_1| \tag{6}$$

The derivative of S_1 and S are then

$$\dot{s}_1 = \tfrac{d}{dt}|T_1| = \frac{d}{dt}\left(x_1^2 + y_1^2 + z_1^2\right)^{1/2} = \frac{x_1\dot{x}_1 + y_1\dot{y}_1 + z_1\dot{z}_1}{s_1} \tag{7}$$

$$\dot{s}_2 = \frac{d}{dt}|T_2| = \frac{d}{dt}|T_1 + \Delta R| \tag{8}$$

$$\begin{pmatrix} \left[(R_0 + h_i)\cos\mu_i \cos L_i\right]\hat{x}, \\ \left[(R_0 + h_i)\cos\mu_i \sin L_i\right]\hat{y}, \\ \left[(R_0 + h_i)\sin\mu_i\right]\hat{z} \end{pmatrix} \quad i = 1, 2 \tag{9}$$

$$\begin{aligned} \Delta R &= \hat{x}[(R_0 + h_1)\cos\mu_1 \cos L_1 - (R_0 + h_2)\cos\mu_2 \cos L_2] \\ &+ \hat{y}\left[(R_0 + h_1)\cos\mu_1 \sin L_1 - \left(R_0 + h_2\right)\cos\mu_2 \sin L_2\right] \\ &+ \hat{z}\left[(R_0 + h_1)\sin u_1 - (R_0 + h_2)\sin\mu_2\right] \\ &\cong \hat{x}\Delta R_x + \hat{y}\Delta R_Y + \hat{z}\Delta R_Z \end{aligned} \tag{10}$$

where

R_0 : Earth radius

h_i : Altitude of T_i above spherical

L_i : Longitude of T_i

μ_i : Latitude of the T_i

Based on the conversion relation of Cartesian coordinate system ($\hat{x}, \hat{y}, \hat{z}$) and spherical coordinate system ($\hat{e}_r, \hat{e}_u, \hat{e}_L$).

$$\begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix} = \begin{bmatrix} \cos u \cos L & -\sin u \cos L & -\sin L \\ \cos u \cos L & -\sin uSINL & \cos L \\ \sin u & \cos u & 0 \end{bmatrix} \begin{bmatrix} \hat{e}_r \\ \hat{e}_u \\ \hat{e}_L \end{bmatrix} = Q \begin{bmatrix} \hat{e}_r \\ \hat{e}_u \\ \hat{e}_L \end{bmatrix} \tag{11}$$

According to Eq(10) and Eq(11), we have

$$\begin{bmatrix} \Delta R_{x_1} \\ \Delta R_{y_1} \\ \Delta R_{z_1} \end{bmatrix} = Q' \begin{bmatrix} \Delta R_x \\ \Delta R_y \\ \Delta R_z \end{bmatrix} \tag{12}$$

$$Q' = \begin{pmatrix} -\sin L & \cos L & 0 \\ -\sin u \cos L & -\sin u \sin L & \cos u \\ \cos u \cos L & \cos u \sin L & \sin u \end{pmatrix} \tag{13}$$

Replacing Eq.(13) into Eq.(12), the transfer matrix using the vector conversion theorem.

$$\begin{pmatrix} \hat{x}_2 \\ \hat{y}_2 \\ \hat{z}_2 \end{pmatrix} = N \begin{pmatrix} \hat{x}_1 \\ \hat{y}_1 \\ \hat{z}_1 \end{pmatrix}, \quad N = \begin{pmatrix} N_{11} & N_{12} & N_{13} \\ N_{21} & N_{22} & N_{23} \\ N_{31} & N_{32} & N_{33} \end{pmatrix} \tag{14}$$

$$
\begin{aligned}
N_{11} &= (-\sin L_1 - \sin L_2) + (\cos L_1 \cos L_2) = \cos \Delta L \\
N_{12} &= \sin u_1 \sin \Delta L \\
N_{13} &= -\cos u_1 \sin \Delta L \\
N_{21} &= \sin u_2 \sin \Delta L \\
N_{22} &= \sin u_1 \sin u_2 \cos \Delta L + \cos u_u \cos u_2 \\
N_{23} &= \sin u_1 \cos u_2 - \sin u_2 \cos u_1 \cos \Delta L \\
N_{31} &= \cos u_2 \sin \Delta L \\
N_{32} &= \sin u_2 \cos u_1 - \cos u_2 \sin u_1 \cos \Delta L \\
N_{33} &= \sin u_2 \sin u_1 + \cos u_2 \cos u_1 \cos \Delta L
\end{aligned} \tag{15}
$$

where

$$
N = \begin{bmatrix} \cos\Delta L_1 & \sin u_1 \sin\Delta L & -\cos u_1 \sin\Delta L \\ \sin u_2 \sin\Delta L_1 & \sin u_1 \sin u_2 \cos\Delta L + \cos u_u \cos u_2 & \sin u_1 \cos u_2 - \sin u_2 \cos u_1 \cos\Delta L \\ \cos u_2 \sin\Delta L & \sin u_2 \cos u_1 - \cos u_2 \sin u_1 \cos\Delta L & \sin u_2 \sin u_1 + \cos u_2 \cos u_1 \cos\Delta L \end{bmatrix} \tag{16}
$$

and $\Delta L = L_1 - L_2 \quad \tan B_2 = \dfrac{x_2}{y_2} \quad \tan E_2 = \dfrac{z_2}{(x_2^2 + y_2^2)^{1/2}}$, so we can find the relation of position, $T_2 = (x_2, y_2, z_2)$ as

$$
\begin{aligned}
x_2 &= \left(x_1 + \Delta R_{x_1}\right) N_{11} + \left(y_1 + \Delta R_{y_1}\right) N_{12} + \left(z_1 + \Delta R_{z_1}\right) N_{13} \\
y_2 &= \left(x_1 + \Delta R_{x_1}\right) N_{21} + \left(y_1 + \Delta R_{y_1}\right) N_{22} + \left(z_1 + \Delta R_{z_1}\right) N_{23} \\
z_2 &= \left(x_1 + \Delta R_{x_1}\right) N_{31} + \left(y_1 + \Delta R_{y_1}\right) N_{32} + \left(z_1 + \Delta R_{z_1}\right) N_{33}
\end{aligned} \tag{17}
$$

Similarly, the velocity detected by the local sensor can be derived. Assume that the velocity of target is $\vec{V}_s = (v_{sx1}, v_{sy1}, v_{sz1})$, Further assume that the velocity of the target detected by the sensor is $\vec{V}_1 = (v_{x1}, v_{y1}, v_{z1})$, the velocity of sensor is $\vec{V}_2 = (v_{x2}, v_{y2}, v_{z2})$, and the velocity of ground central system is $\vec{V}_2 = (0,0,0)$ as it is fixed. Then the velocity of the central ground system can be computed as

$$
\begin{aligned}
&\Delta V = \vec{V}_1 - \vec{V}_2 = \left(v_{x1} - 0, v_{y1} - 0, v_{z1} - 0\right) = \vec{V}_1 = \\
&\vec{v}_x[(R_0 + h_1)\cos\mu_1 \cos L_1 - (R_0 + h_2)\cos\mu_2 \cos L_2] \\
&+\vec{v}_y\left[(R_0 + h_1)\cos\mu_1 \sin L_1 - (R_0 + h_2)\cos\mu_2 \sin L_2\right] \\
&+\vec{v}_z\left[(R_0 + h_1)\sin u_1 - (R_0 + h_2)\sin\mu_2\right] \\
&\cong \vec{v}_x \Delta V_x + \vec{v}_y \Delta V_Y + \vec{v}_z \Delta V_Z
\end{aligned} \tag{18}
$$

where R_0, h_i, μ_i, L_i are defined in Eq.(10).

Assume

$$
\begin{bmatrix} \Delta V_{x1} \\ \Delta V_{y1} \\ \Delta V_{z1} \end{bmatrix} = Q \begin{bmatrix} \Delta V_x \\ \Delta V_y \\ \Delta V_z \end{bmatrix} \tag{19}
$$

and

$$
\begin{pmatrix} \vec{V}_2 \\ \vec{V}_2 \\ \vec{V}_2 \end{pmatrix} = N \begin{pmatrix} \vec{V}_1 \\ \vec{V}_1 \\ \vec{V}_1 \end{pmatrix} \tag{20}
$$

We can find the relation of velocity:

$$
\begin{aligned}
v_{sx2} &= \left(v_{sx1} + \Delta V_{x1}\right) N_{11} + \left(v_{sy1} + \Delta V_{y1}\right) N_{12} + \left(v_{sz1} + \Delta V_{z1}\right) N_{13} \\
v_{sy2} &= \left(v_{sx1} + \Delta V_{x1}\right) N_{21} + \left(y_{sy1} + \Delta V_{y1}\right) N_{22} + \left(v_{sz1} + \Delta V_{z1}\right) N_{23} \\
v_{sz2} &= \left(v_{sz1} + \Delta V_{x1}\right) N_{31} + \left(y_{sy1} + \Delta V_{y1}\right) N_{32} + \left(v_{sz1} + \Delta V_{z1}\right) N_{33}
\end{aligned} \tag{21}
$$

4. Multi-Sensor Fusions Algorithm

Suppose that a system distributes N sensors, the district of prognosticate has L targets, and the ith sensor have L_i targets the dynamic state model of dispersed time and measurement model were define. The dynamic state model of the central processing system has the following form:

$$
\begin{aligned}
&X(k+1) = F(k)X(k) + G(k)W(k) \\
&Y_i(k) = C_i(k)X(k) + V_i(k), \quad i = 1, \ldots\ldots, N
\end{aligned} \tag{34}
$$

Also, the sensor model of the central processing system has the form of:

$$
\begin{aligned}
&X_i(k+1) = F_i(k)X_i(k) + G_i(k)W_i(k) \quad i = 1, \ldots. N \\
&Y_i(k) = H_i(k)X(k) + V_i(k), \quad i = 1, \ldots\ldots, N
\end{aligned} \tag{35}
$$

Also let sensor model of the central processing system be written as:

$$
C_i(k) = H_i(k)M_i(k) \tag{36}
$$

In order to combine the sensor data with one data form the central processor the coordinate of $X_i(k+1)$, $Y_i(k)$ and $C_i(k)$ has to be performed.

Assume that:

$$
Y(k) = \begin{bmatrix} Y_1(k) \\ Y_2(k) \\ \vdots \\ Y_{L_i}(k) \end{bmatrix}, C(k) = \begin{bmatrix} C_1(k) \\ C_2(k) \\ \vdots \\ C_N(k) \end{bmatrix}
$$

$$
R(k) = diag[R_1(k), \ldots\ldots, R_N(k)]
$$

The global estimate can be computed with a Kalman filter:

$$
\hat{X}_f(k \mid k) = \hat{X}_f(k \mid k-1) + K(k)[Y(k) - C(k)\hat{X}_f(k \mid k-1)] \tag{37}
$$

$$
K(k) = P_f(k \mid k-1)C^T(k) \cdot [C(k)P_f(k \mid k-1)C^T + R(k)]^{-1} \tag{38}
$$

$$
P_f(k \mid k) = [I - K(k)C(k)]P_f(k \mid k-1) \tag{39}
$$

$$
\hat{X}_f(k+1 \mid k) = F(k)\hat{X}_f(k \mid k) \tag{40}
$$

$$
P_f(k \mid k-1) = F(k)P_f(k-1 \mid k-1)F^T(k) + G(k)Q(k)G^T(k) \tag{41}
$$

In order to combine the results obtained form the central system and those from local system,we define the fusion matrix $B_f(k)$ as follows:

$$
B_f(k) = [\sum_{i=1}^{N} M_i^T(k)M_i(k)]^{-1} \tag{42}
$$

$$
\hat{X}_f(k \mid k) = A_f(k)\hat{X}_f(k-1 \mid k-1) + \sum_{i=1}^{N} K_i(k)Y_i(k) \cdot B_f(k) \tag{43}
$$

where

$$A_f(k) = [I - \sum_{i=1}^{N} K_i(k)C_i(k) \cdot B_f(k)]F(k) \qquad (44)$$

and

$$K_i(k) = P_f(k|k-1)C_i^T \cdot [C_i(k)P_f(k|k-1)C_i^T + R_i(k)]^{-1} \qquad (45)$$

Moreover, we need combine the tracking the algorithm of local system for the estimation.

The local value of the estimate is calculated also by Kalman filter as follows:

$$\hat{X}_{if}(k|k) = A_{if}(k)\hat{X}_{if}(k-1|k-1) + K_{if}(k)Y_i(k) \qquad (46)$$

$$A_{if}(k) = [I - K_{if}(k)H_i(k)]F_i(k) \qquad (47)$$

$$K_{if}(k) = P_{if}(k|k-1)H_i^T \cdot [H_i(k)P_f(k|k-1)H_i^T + R_i(k)]^{-1} \qquad (48)$$

$$P_{if}(k|k-1) = F_i(k)P_{if}(k-1|k-1)F_i^T + G_i(k)Q_i(k)G_i^T(k) \qquad (49)$$

Rearranging Eq.(46), we have

$$K_{if}(k)Y_i(k) = \hat{X}_{if}(k|k) - A_{if}(k)\hat{X}_{if}(k-1|k-1) \qquad (50)$$

$$K_i(k)Y_i(k) = \Phi_i\{\hat{X}_{if}(k|k) - A_{if}(k)\hat{X}_{if}(k-1|k-1)\} \qquad (51)$$

where

$$\Phi_i(k) = P_f^{-1}(k|k)M_i^T(k)P_{if}(k|k) \qquad (52)$$

Applying these results into Eq(51), we can obtain:

$$\hat{X}_f(k|k) = A_f(k)\hat{X}_f(k-1|k-1) + \sum_{i=1}^{N}\Phi_i(k)\left[\hat{X}_{if}(k|k) - A_{if}(k)\hat{X}_{if}(k-1|k-1)\right] \cdot B_f(k)$$
$$= SI(k|k) + \sum \Phi_i(k)\hat{X}_{if}(k|k) \cdot B_f(k) \qquad (53)$$

where

$$SI(k|k) = A_f(k)\hat{X}_f(k-1|k-1) - \sum_{i=1}^{N} T_i(k)\hat{X}_{if}(k-1|k-1) \cdot B_f(k) \qquad (54)$$

and

$$T_i(k) = \Phi_i(k)A_{if}(k) \qquad (55)$$

Data fusion is the center of multi-target system. When tracking multi-target happen mutual overlap, data fusion is the best way to solve the problem.

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. 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. The performance of multiple-target tracking in the planar case was simulated under several different situations. In order to compare the performance of different algorithm, we simulated each situation by two different approaches. Method1: Using an adaptive tracking algorithm together with a data association technique.Method2: Using an adaptive estimator for tracking algorithm proposed in this paper.

First, the simulations of tracking multiple targets are presented in Figure 4 and Figure 5. Its initial conditions and maneuvering situations are shown in Table 1 and Table 2 respectively. After using Monte Carlo fifty runs, we have the simulation results whose average tracking errors are shown in Table 3. Moreover, the position and velocity errors are shown in Figure 6 and figure 7, respectively. According to the simulation results, the proposed tracking algorithm in this paper works quite well and better.

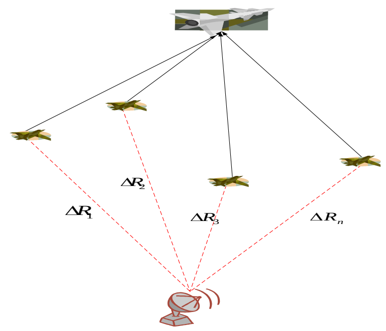

Figure 1 Radar tracking system diagram

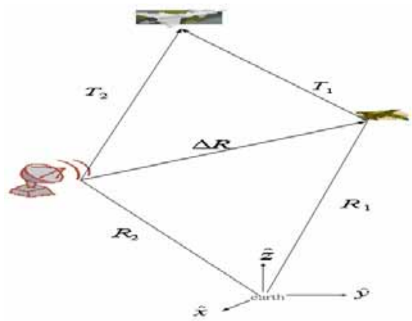

Figure 2 Sensor system coordinate diagram

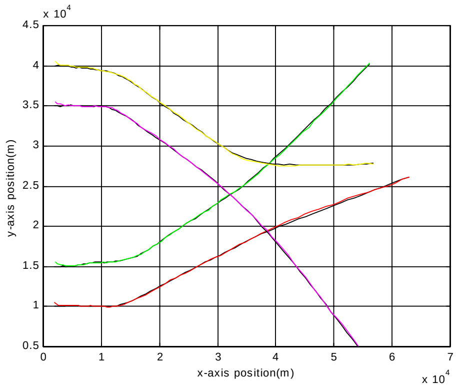

Figure 4 Simulation of tracking Multiple targets (Method 1)

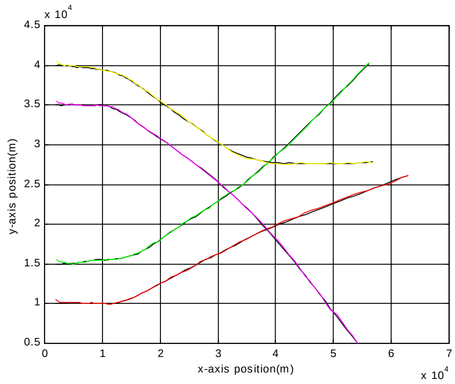

Figure 5 Simulation of tracking Multiple targets (Method 2)

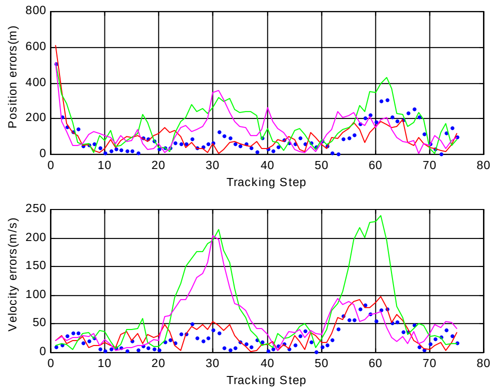

Figure 6 Performance error tracking Multiple targets (Method 1)

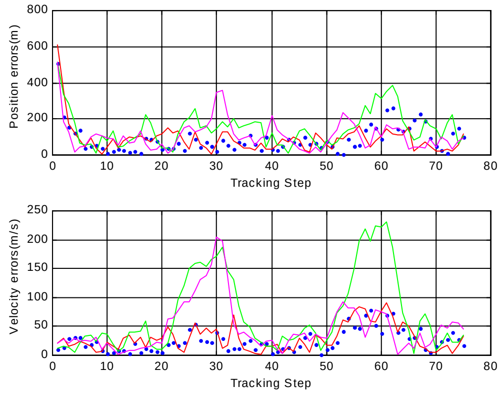

Figure 7 Performance error tracking Multiple targets (Method 2)

Table 1 Initial Condition of Multiple Targets

	$X(m)$	$\dot{X}(m/s)$	$Y(m)$	$\dot{Y}(m/s)$
Target 1	2000	450	10000	0
Target 2	2000	450	15000	0
Target 3	2000	450	35000	0
Target 4	2000	450	40000	0

Table 2 Target Acceleration Conditions of Multiple Targets

	20~30 Step		50~60 Step		Other Step	
	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)	$a_y(m/s^2)$
Target 1	30	30	20	0	0	0
Target 2	20	30	20	30	0	0
Target 3	30	-30	20	-30	0	0
Target 4	30	-30	20	30	0	0

Table 3 Simulation Results of Tracking Multiple Targets

		Target 1	Target 2	Target 3	Target 4
Method 1	Position rms error(m)	96.92	93.17	136.00	126.43
	Velocity rms error(m/s)	25.38	33.05	73.3221	51.73
Method 2	Position rms error(m)	86.94	88.34	146.6107	107.89
	Velocity rms error(m/s)	23.93	28.61	51.77	46.56

6. Conclusion

An improved algorithm for tracking multiple maneuvering targets was accomplished in this paper. This approach is implemented with a dynamic sensor system for the radar surveillance, by installing the sensors in moving systems, such as airplanes and ships, so that. Moreover, using the multiple sensor fusion algorithms will reduce the misdetection probability. According to the simulation results, it shows that this algorithm was capable of tracking multiple targets in various situations, and has good performance also.

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