NEW PROPOSED ALGORITHM FOR SINGLE SENSOR MULTI-TARGET TRACKING IN DENSE ENVIRONMENTS

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ABSTRACT

A significant problem in multi-target tracking (MTT) is the observation-to-track data association. An observation is a signal received, from a target or background clutter, which provides positional information. If an observation is incorrectly associated with a track, that track could diverge and prematurely terminate or cause other tracks to also diverge. Mainly, there are two basic approaches used in data association: the nearest neighbor (NN) approach and the all-neighbors (AN) approach. In the NN approach, the track is updated by at most one observation but in the AN approach, weights are assigned for reasonable observations and a weight centroid of those observations is used to update the track. This paper introduces two techniques belonging to the AN approach: the probabilistic data association (PDA) technique and a new proposed technique. Examples are given to compare the PDA algorithm with the proposed algorithm for data association.

Keywords

Multi-target Tracking, Data Association.

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I. Introduction

Data association is one of the most important tasks in multi-target tracking (MTT) systems. The topic data association deals with the integration of measurements (observations) from different sensors (multi-sensor-MTT) or from one sensor (single sensor-MTT) at different time instants. This paper is concerned with collection of measurements from single sensor. There are always ambiguities in associating between extracted positional data to previously known targets. In addition in a cluttered environment, the observation signals may not all arise from targets of interest. Some of them may be from clutter or due to false alarms. In order to estimate the parameters of the targets, one needs to associate each measurement to a unique target or to declare the measurement as clutter. If an observation is incorrectly associated to a track, it could diverge this track and causes other tracks to also diverge.

Mainly, there are two basic approaches used in data association [3]: the nearest neighbor (NN) approach and the all-neighbors (AN) approach. The NN approach looks for a unique pairings where, at most, a single observation is associated to a given track in a manner that minimizes some distance error criterion. The AN approach incorporates all observations within the neighborhood, as defined by the gate around the predicted target position. Then the updated position is based on the weighted sum of all observations. Such weight is calculated using probability theory [2].

This paper discusses the probabilistic data association (PDA) technique. A new proposed technique for data association belonging to the AN approach is introduced. The performance of the proposed algorithm is compared with the original PDA algorithm to show its simplicity and robustness.

2. Modeling 2-D Multi-Target Tracking Problem

In two-dimensional tracking system, target dynamics may be represented by the vector-matrix equation of the form

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

where

$$X(k) = \begin{bmatrix} x(k) \\ y(k) \\ \dot{x}(k) \\ \dot{y}(k) \end{bmatrix} \quad F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad G = \begin{bmatrix} T^2/2 & 0 \\ 0 & T^2/2 \\ T & 0 \\ 0 & T \end{bmatrix}$$

$x(k)$ and $y(k)$ are target coordinates.
$\dot{x}(k)$ and $\dot{y}(k)$ are the velocities of target in the x and y directions.
F and G are transition matrices.
T is the sampling interval.
k is the time instant.
$a(k)$ is random acceleration acting on the target and it is assumed to be zero mean white Gaussian noise with known covariance matrix

$$E\{a(k)a^T(j)\} = Q(k)\delta_{kj} \tag{2}$$

where

$$Q = \begin{bmatrix} \sigma_a^2 & 0 \\ 0 & \sigma_a^2 \end{bmatrix} \tag{3}$$

The random acceleration is assumed to be of equal variance and also independent along x and y axes.

The measurement model of such target by a single sensor is described as follows

$$Z(k) = \begin{cases} HX(k) + V(k) & \text{when measurement originates from target} \\ \\ C(k) & \text{when measurement originates from clutter} \end{cases} \tag{4}$$

where

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{5}$$

$V(k)$ is the measurement error, and is assumed to be zero mean Gaussian noise with covariance matrix of the form

$$E\{V(k)V^T(j)\} = R(k)\delta_{kj} \tag{6}$$

where

$$R = \begin{bmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{bmatrix} \tag{7}$$

σ_x and σ_y are standard deviations of measurement errors in both x and y directions.

The number of the clutter observations in a single scan, n, are assumed to have a Poisson distribution that

$$P(n) = \frac{(b)^n}{n!} e^{-b} \tag{8}$$

Where

b is average number of clutter observations per scan;

Target locations are assumed to have a uniform distribution on the surveillance region [6,8].

If we assume that the number of received observations in recent scan is $N(k)$, the problem is to estimate a state vector of each target, $\hat{X}(k/k)$, based on the observations in the scan k; $Z(k)=\{Z_j(k), j=1, 2,........,N\}$. It is required to associate each observation to its true previously estimated track. However, in most MTT situations, more than one observation is within the track gate or one observation is within the gates of more than one track as shown in Fig. 1. where P_i is the predicted position of the ith target and O_j is the jth observation. The circle around the predicted track denotes the gate in which possible future position of the target is predicted.

Mathematically, a validation gate is defined by [1, 3, 6]

$$e_{ij}(k)S^{-1}(k)e_{ij}^{T}(k) \leq g^{2} \tag{9}$$

Where g^2 is a selected threshold (gate size) and $e_{ij}(k)$ is the measurement residual (innovation) [3] defined by

$$e_{ij}(k) = \left[Z_j(k) - H\hat{X}_i(k/k-1) \right] \tag{10}$$
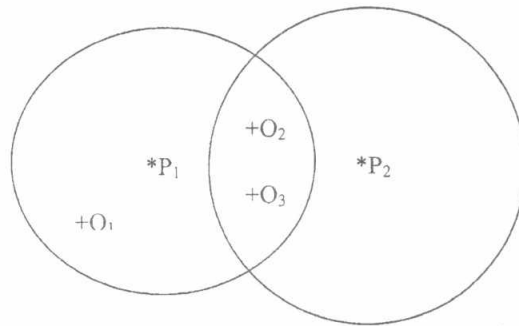
O$_{1,2,3}$ .... Observation positions
P$_{1,2}$ ..... Predicted positions
Fig.1   Example of a complex conflict situation

With residual covariance matrix defined by

$$S_i(k) = H\,P(k/k-1)H^{T} + R \tag{11}$$

where

$\hat{X}(k/k-1)$ is the estimate of the state vector before processing the measurement $Z(k)$, and

$P(k/k-1)$ is the covariance matrix of estimation error before processing the measurement $Z(k)$

There exist many ways to define the gate size, but as discussed in [2, 5], the choice of g according to (12) ensures that the correct measurements will lie within the gate with probability 0.999.

$$g > \sqrt{M} + 2 \tag{12}$$

M is the dimension of the measurement vector $Z(k)$. Thus any observations do not satisfy the inequality given in equation (9) are outside the gate and must be eliminated.

3. Review of the Probabilistic Data Association (PDA) Technique

Probabilistic data association (PDA) was first proposed by Bar-Shalom and Tse [2]. A detailed derivation of the PDA technique can be found in [2,4,5] and is briefly described here. When using PDA, the update equation of the target position estimate becomes:

$$\hat{X}(k/k) = \hat{X}(k/k-1) + K(k)e_i(k) \tag{13}$$

where K(k) is the Kalman gain and given by

$$K(k) = P(k/k-1)H^T\left[HP(k/k-1)H^T + R\right]^{-1} \tag{14}$$

and

$$e_i(k) = \sum_{j=1}^{N} P_{ij}e_{ij}(k) \tag{15}$$

the probability that the jth observation came from the current target in track is P_{ij} and is given by

$$P_{ij} = \begin{cases} \dfrac{c}{c + \sum\limits_{l=1}^{N}\alpha_{il}}, & j=0 \text{ (no valid observation)} \\[2ex] \dfrac{\alpha_{ij}}{c + \sum\limits_{l=1}^{N}\alpha_{il}}, & 1 \le j \le N \end{cases} \tag{16}$$

where

$$c = (1 - P_D P_G)b(2\pi)^{M/2}\sqrt{|S_i|} \tag{17}$$

$$\alpha_{ij} = P_D e^{-\frac{d_{ij}^2}{2}} \tag{18}$$

$$d_{ij}^2 = e_{ij}^T S^{-1} e_{ij} \tag{19}$$

P_D is the probability of target detection; P_G is the probability that a target return falling within the validation gate. Assume the gate is sufficiently large that the target return will fall within the track gate (P_G=1.0), and M is the dimension of the measurement vector.
The update covariance matrix is given by

$$P(k/k) = \left[I - K(k)H\right]P(k/k-1) + dP(k) \tag{20}$$

where

$$dP(k) = K(k)\left[\sum_{j=1}^{N} P_{ij}e_{ij}(k)e_{ij}^T(k) - e(k)e^T(k)\right]K^T(k) \tag{21}$$

The term *dP(k)* increases the covariance according to both a posteriori probabilities (or uncertainties) and the spread of the observations found within the track gate. The significant problem of the PDA method is that it assumes all observations in a particular extension gate, either the observations from the target or random clutter

points. If an observation from another target is present in this optimum target extension gate, the probability calculation is wrong and poor tracking results [7]. Thus, it may fail in tracking closely spaced targets but it may give good results in tracking multiple targets far from each other.

4. Proposed Algorithm for Data Association

In this section a proposed algorithm for solving the problem of observation-to-track data association in MTT is proposed. It depends on the AN approach, like the PDA, because the updated position of the target is based on a weighted sum of all observations within the validation gate by giving a probability weight to each observation. This probability weight depends on measuring the distance from the predicted target position and each observation within its validation gate.

The only difference among the PDA technique and the proposed technique is the method of calculating the probability weights P_{ij}.

In this proposed technique we assume that the probability of track i being associated with observation j is defined by

$$P_{ij} = \begin{cases} 0 & j=0 \text{ (no valid observation)} \\ \dfrac{1 - D_{ij}\Big/\sum_{j=1}^{N} D_{ij}}{N-1} & 1 \le j \le N \end{cases} \tag{22}$$

where
  D_{ij} is the distance measured between the jth observation   and track i which is given by

$$D_{ij} = \sqrt{(\hat{x}_i - x_j)^2 + (\hat{y}_i - y_j)^2} \tag{23}$$

This proposed formula for calculating P_{ij} gives a high weight to the measurement closest to the predicted position of the target. Further more this weight decreases as the measurement position is far from the predicted position of the target. After computing the weigts using equation (22), the state updating equation in Kalman filter uses the combined innovation as in PDA method which is defined as the weighted sum of the residuals associated with N observations as in equation (15).

The covariance matrix, $P(k/k-1)$, of estimation errors before processing the measurement $Z(k)$ is recursively computed as

$$P(k+1/k) = FP(k/k)F^T + GQG^T \tag{24}$$

The calculation of covariance matrix of estimated errors after processing the observations, $P(k/k)$, is as in PDA method and is given by

$$P(k/k) = [I - K(k)H(k)]P(k/k-1) \tag{25}$$

Equations (22) through (25) define the proposed algorithm. It is clear that, this new proposed technique simplifies the probability calculations, P_{ij}, compared with the PDA technique.

5. COMPUTER SIMULATION

A Monte Carlo simulation of 100 runs was performed and the values of the estimation errors are computed and averaged by the number of runs. Here, we present the results for three representative scenarios:

1. single target tracking
2. Tracking of Two Crossing Targets at low Angle
3. Two Parallel Targets Tracking

5.1 Single Target Tracking

Consider a target moving on a straight line path and its initial state is X(0)=[6000m 6000m 150m/s 60m/s]^T. The sampling time, T, is 0.1 second during simulation with 1000 samples are considered. Fig. (2) shows the tracking error in position between the true trajectory and the estimated trajectory of the target, as function of time for the PDA and proposed techniques in the case of clutter density, b=0.01. and $\sigma_x = \sigma_y = 30$ m.

As shown from Fig. (2), the two techniques have the same performance For better comparison, the tracking root mean square (rms) errors of position are computed as 6m for both of the two algorithms.

5.2 Tracking of Two Crossing Targets at Low Angle

Let us consider two target trajectories crossing in low angle. The initial states of the targets are $X_1(0)$=[7000m 7000m 130m/s 40m/s] and $X_2(0)$=[7000m 8000m 110m/s 0m/s] and they are perfectly known. The sampling time, T, is 1 second during simulation with 100 samples are considered and the value of σ_x and σ_y will be set at 50m.The performance of the two techniques is shown in figures (3) and (5) where both the true tracks of the targets are plotted as doted lines and the corresponding estimated ones are plotted as solid lines. The clutter is assumed to be of density 0.01.

As shown from figures (3) and (4), the PDA technique has failed in tracking two crossing targets in low crossing angle, one track is lost. The new proposed technique is quite successful in tracking the two targets. The proposed technique has 30m rms error for both targets. Of course it is more than the rms error obtained in the previous scenario of single target but it is still acceptable. Fig. (5) shows that the error between estimated and true trajectories is decreasing with time. This is due to the performance of Kalman filter in prediction.

5.3 Two Parallel Targets Tracking

Let us consider the case where two targets flying parallel to each other. The initial states of the targets are $X_1(0)=[6000m \quad 6000m \quad 150m/s \quad 60m/s]$ and $X_2(0)=[7000m \quad 7000m \quad 150m/s \quad 60m/s]$ and they are perfectly known. The sampling time, T, is 1 second during simulation with 100 samples are considered and the value of σ_x and σ_y will be set at 50m. The performance of the two techniques in tracking two parallel targets is illustrated in figures (6) and (7). The PDA technique lost the tracking of the two targets. The proposed technique tracked the two parallel targets successfully.

The convergence of the Kalman filtering in the proposed technique is shown in figure (8). This figure shows that the error between estimated and true trajectories is decreasing with time. This is due to the performance of Kalman filtering prediction.

6. Conclusions

In this paper, we have proposed a new technique for data association depending on the all neighbor (AN) approach to track multi-targets in a cluttered environment. The proposed algorithm depends on a single sensor and successive observations to estimate the future position of the target. The proposed algorithm utilizes all the available observations within the validation gate and associates a probabilistic weight to each of them to obtain the estimated position of the target. The proposed technique is a simpler application of the AN approach than the original PDA algorithm. The computation of the probabilistic weights is a linear function of the distance between the prepredicted position of the target and the available observations. The proposed algorithm has better performance compared with the PDA technique, in case of dense environments where more than one target is presented in the same tracked region. Moreover, the proposed algorithm succeeded in tracking two closely spaced targets in heavy clutter density. While, the PDA method fails to track two closely spaced targets even in low clutter density.

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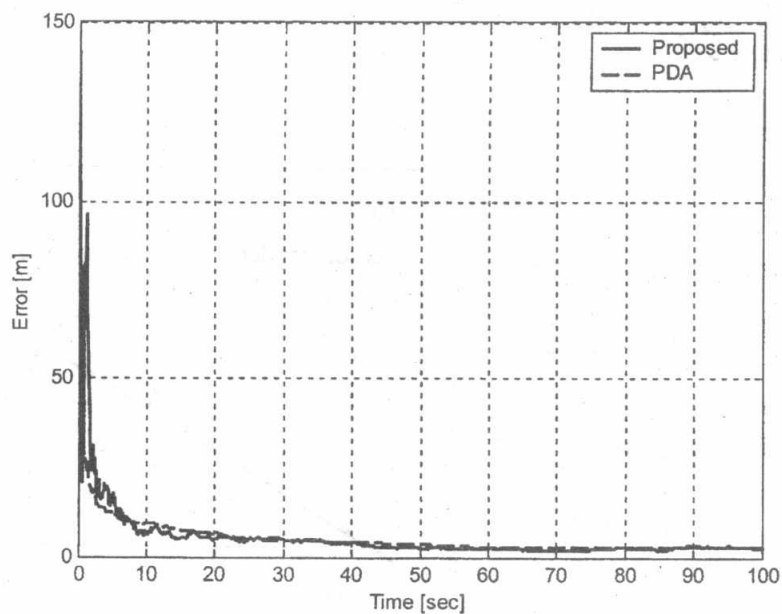
Fig.2.The tracking error for the two simulated techniques ($\sigma_x = \sigma_y = 30$ m)
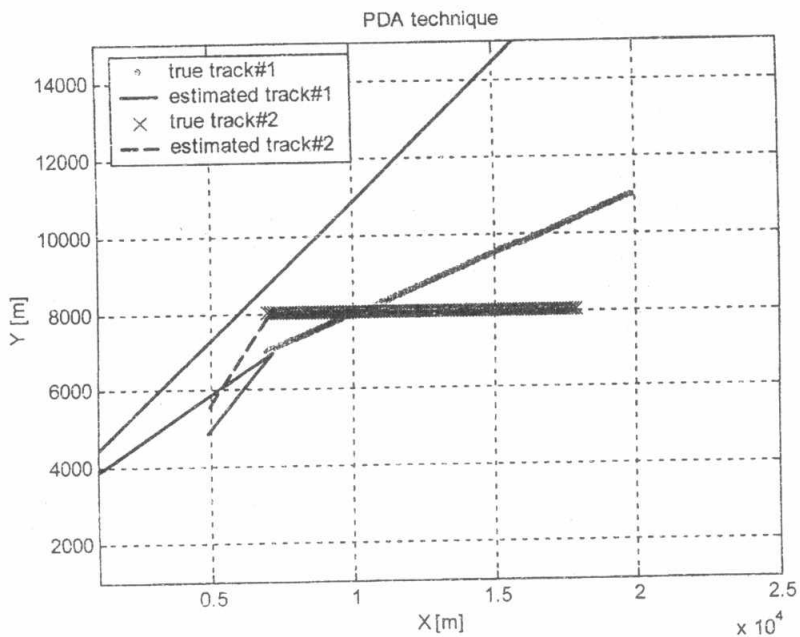
PDA technique

Fig.3.Failure of PDA in two crossing targets tracking in low angle (b=0.01)

Proposed technique

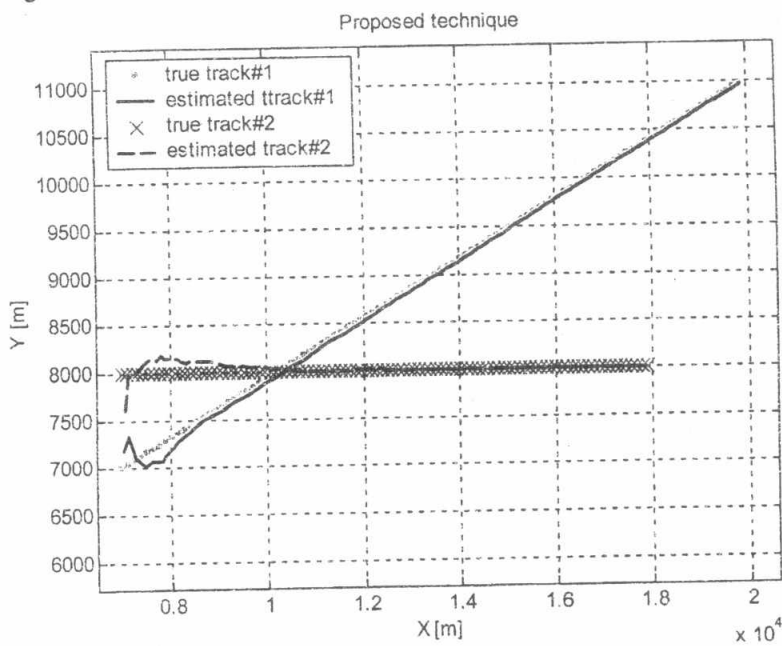

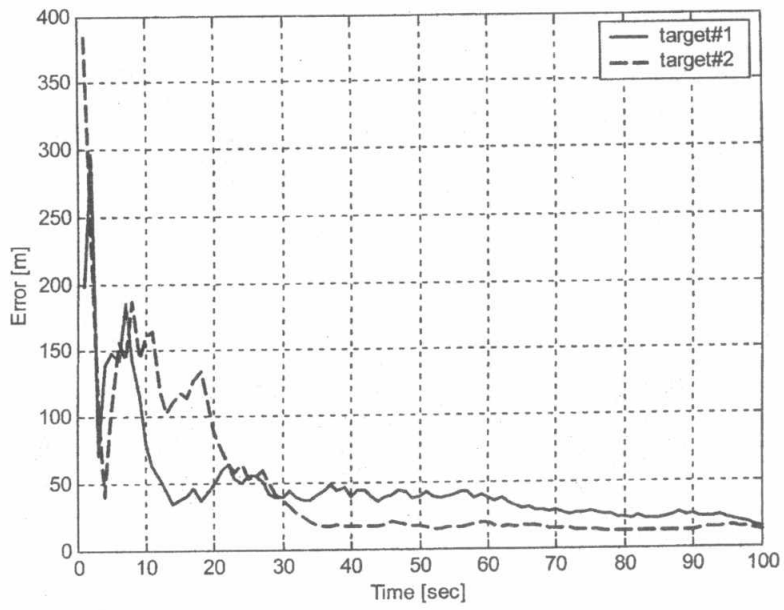Fig.4.Tracking two crossing targets in low angle by the proposed technique (b=0.01)

Fig.5. Error between estimated and true trajectories in the new technique for tracking
two crossing targets at low angle
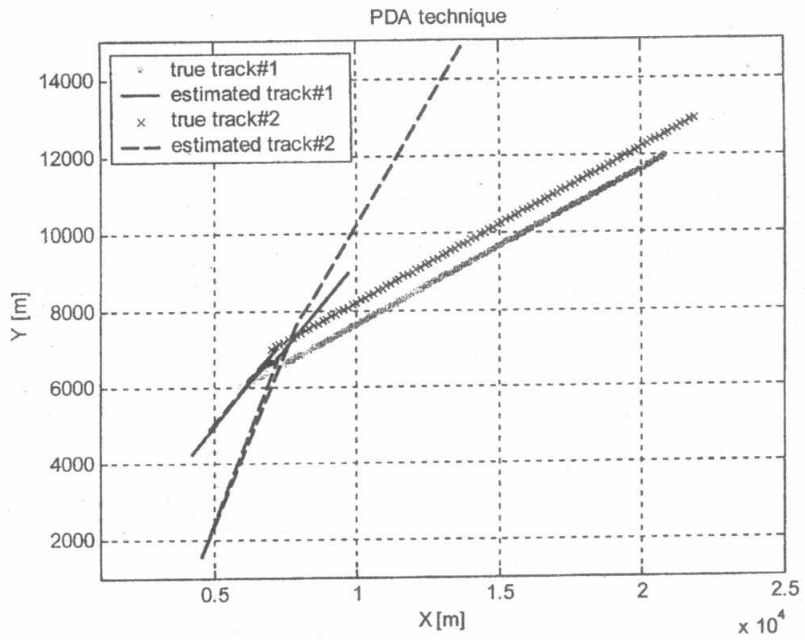$(\sigma_x = \sigma_y = 50 \text{ m}, b=0.01)$

Fig. 6   Failure of PDA algorithm in two parallel targets tracking (b=0.01)
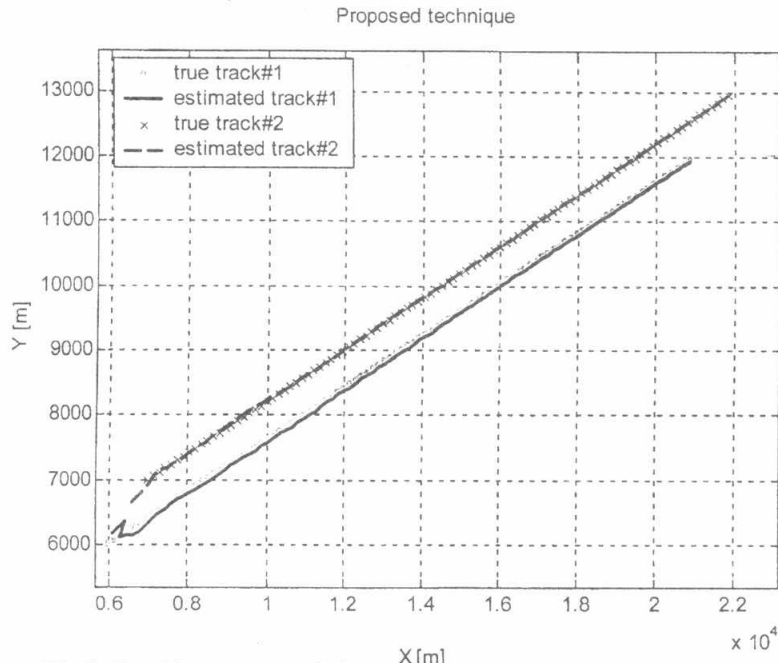
Proposed technique

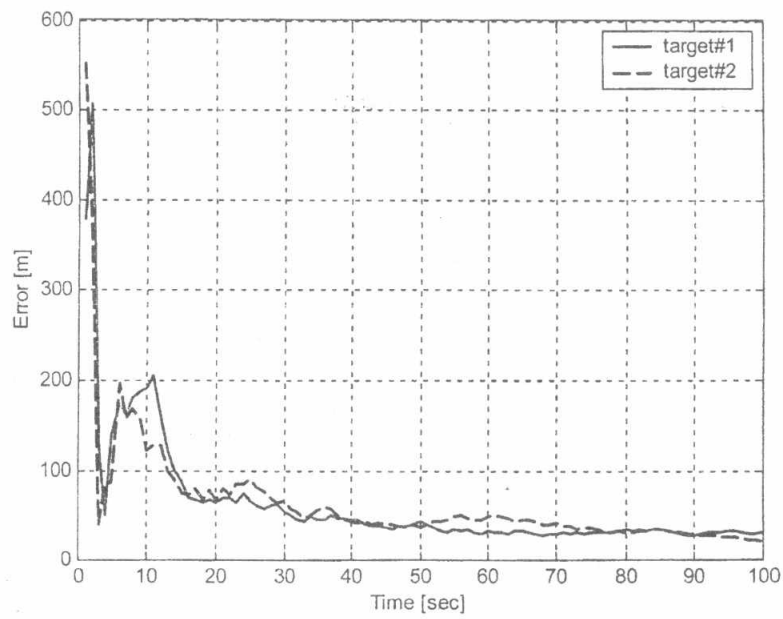Fig.7. Tracking two parallel targets by the proposed technique (b=0.01)

Fig. 8 Error between estimated and true trajectories in the new technique for tracking two parallel targets ($\sigma_x = \sigma_y = 50$ m , b=0.01)