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Multi-target Tracking in a Test Range Scenario

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ABSTRACT

Integrated Test Range (ITR) handles various types of multiple-target flight trials. To facilitate target tracking and estimation in such multi-target scenario, nearest neighbourhood (NN) technique-based data association algorithm has been adopted at ITR. The present paper discusses the NN-based data association algorithm and its performance in a real flight trial situation by using multiple-target track data from a multi-target tracking radar.

Keywords: Multi-target tracking, data association, nearest neighbourhood, test range, flight vehicles developmental trials, post flight performance analysis, real-time flight safety measurement

1. INTRODUCTION

Integrated Test Range (ITR), Chandipur, handles test and evaluation of short-range, medium-range and long-range guided missiles, rockets and various other airborne objects. Ensuring safety of life and properties in and around the launch corridor is an indispensable requirement during test and evaluation of these developmental flight vehicles. This necessitates monitoring the consistency of the flight vehicle's trajectory and health status in real time wrt the desired one. This, in turn, is possible using an efficient tracking and estimation algorithm which extracts useful information from multiple-tracking sensors' noisy measurement data for the purpose of real-time flight safety monitoring as well as for post-flight performance analysis.

The different flight scenarios encountered at ITR are engagement of multiple targets by multiple missiles, ejection of multiple payloads, engagement of air-to-air missiles, etc. In view of this, the target tracking and estimation algorithm should be capable of detecting and tracking different targets by utilising the measurements from various sensors. In a multi-target tracking situation, a single sensor or a number of sensors can observe multiple targets at a time. Assessment of the actual scenario in such situations becomes complicated as opposed to single target tracking due to uncertain origin of the data and disparate data sources. In addition to the presence of noise of unknown measurement or partially known statistical properties, the source responsible for each measurement is unknown in this case. Hence, there is uncertainty as how to associate data from one sensor, which is obtained at one time, and location to that of another sensor at another point in time and location. Tracking is further complicated by the fact that some sensors may not observe the targets due to the variation of signals and the sensor characteristics. The situation gets further complex in the presence of false alarm and clutter and when the number of targets is also unknown. In a dense target scenario, it is very difficult to associate a measurement with its source (even

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when each of the targets is resolved by the sensors) with certainty. On the other hand, the inherent limitations of the tracking sensors may fail to resolve closely-spaced targets, and thus, inhibit appropriate assessment of target scenario. Hence, the central problem in multi-target tracking is data association, i.e., identifying the target responsible for individual measurement. Further, the algorithm must have efficient methodology for track initiation, confirmation, and deletion.

Gating and data association enable tracking in multi-sensor multi-target scenarios. Gating helps in deciding if an observation (which includes clutter, false alarms, and electronic countermeasures) is a probable candidate for track maintenance or track update. Data association is a step to associate the measurements to the targets with certainty when several targets are in the same neighbourhood.

Commonly used association metrics are distance measure, association coefficient, correlation coefficient, probabilistic similarity measures[1,2], etc. Based on these techniques, there are a number of non-Bayesian and Bayesian algorithms for tracking in multiple-target environment[1-8], e.g., track-splitting approach, nearest neighbourhood (NN) method, maximum likelihood method, joint probabilistic data association approach, multi-hypothesis tracking, etc.

In track-splitting approach, a track is split whenever more than one detection is observed in the neighbourhood of the predicted measurement. The likelihood function of each trajectory is computed and the track is dropped when the likelihood value is less than a predetermined threshold. It yields all the reasonably likely tracks. On the contrary maximum likelihood method yields sets of most likely tracks. However, these non-Bayesian algorithms do not consider the probability of measurement origin uncertainty.

The Bayesian approach takes into account either prior or posterior probability regarding the measurement origin uncertainty. For the application environment at ITR, where the number of targets are limited (not a very dense target scenario), NN-based algorithm has been adopted for its simplicity as well as efficiency for the intended scenario. In this algorithm, measurements are assigned to the tracks by defining a measure of association that quantifies the closeness between measurement pairs or measurement-to-track pairs.

2. ALGORITHM ADOPTED AT ITR

The nearest neighbourhood technique (based on distance measure) for data association has been adopted at ITR for the purpose of identifying measurement-to-target pairs. This technique aims at providing target information by resolving target-measurement pairings in a multi-target multi-sensor scenario. This algorithm is based on likelihood theory and the goal is to minimise an overall distance function that considers all observation to track pairing which satisfies a preliminary gating test. As the number of targets are not known *a priori*, track-oriented approach is adopted for the present application. The different steps of NN algorithm adopted at ITR are shown in Fig. 1 and are discussed below.

Sensors I=1,2.....,i track the targets J=1,2.....,j and produce the measurement set $Y_k^I = \left\{ y_k^n \right\}_{n=1}^{i}$ at k^{th} instant. $X_k^J = \left\{ x_k^m \right\}_{m=1}^{j}$ represents the set of the target tracks at k^{th} instant.

2.1 Data Alignment

Measurements from different sensors y_k^i are available in different sensor-specific coordinate frame, in different data rates and wrt respective sensor locations. These data are converted into a uniform temporal and spatial reference.

2.2 Gating

This step aims at finding possible measurement y_k^i to target x_k^j pairings based on the likelihood of the predicted target position and the measurement based on Chi-square threshold. This uses state prediction covariance and innovation covariance obtained from Kalman filter. This defines the gate G such that the correlation is allowed if the following relationship is satisfied:

$$d_{i,j}^2 = \tilde{y}_k^{i,j} \left(S_k^{i,j} \right)^{-1} \left(\tilde{y}_k^{i,j} \right)^T \leq G \tag{1}$$

where, $d_{i,j}^2$ is the norm of measurement residual for measurement y_k^i from i^{th} sensor and target state x_k^j for j^{th} track.

$$\tilde{y}_k^{i,j} = y_k^i - H^{i,j}\hat{x}_{k|k-1}^j$$

In the above equation, $\tilde{y}_k^{i,j}$ is measurement residual at k^{th} instant for measurement from i^{th} sensor and target state x_k^j for j^{th} track, y_k^i is measurement at k^{th} instant from i^{th} sensor, $\hat{x}_{k|k-1}^j$ is predicted state at k^{th} instant for j^{th} track, and $H^{i,j}$ is measurement matrix for i^{th} sensor and j^{th} track.

$$S_k^{i,j} = H^{i,j}P_{k|k-1}^j\left(H^{i,j}\right)^T + R^i \quad (2)$$

In the above equation, $S_k^{i,j}$ is covariance matrix of measurement residual at k^{th} instant for measurement y_k^i from i^{th} sensor and target state x_k^j for j^{th} track, $P_{k|k-1}^j$ is covariance matrix for state prediction error at k^{th} instant for j^{th} track, and R^i is covariance matrix of measurement error for i^{th} sensor.

Assuming the components of measurements (i.e., measurement in x, y and z-directions) to be independent and measurement noise and process noise to be zero mean and Gaussian and independent of each other, $\tilde{y}_k^{i,j}$ becomes zero mean and Gaussian. Hence, $d_{i,j}^2$ (as defined above) being sum of square of M (number of components of measurements = 3 in present case) independent zero-mean unity variance Gaussian random variable is a random variable with Chi-square distribution. Assuming allowable probability of valid observation falling outside the gate G, the value of G can be determined by Chi-square table and the following relation:

$$\text{Probab } [\chi_M^2 > G] = 1 - P_G, \quad (3)$$

where, P_G = probability of valid observation falling within the gate. Hence, for a particular M, the size of gate is decided by P_G and the performance of the NN algorithm is affected by the value of P_G.

2.3 Correlation

This is the process to update target information based on the associated measurements to the target in a situation where either one measurement satisfies the gate of more than one target, or more than one measurement satisfies the gate of one target, or no measurement fulfils the gating criteria of a particular target. The process of correlation is executed in NN by minimising an overall distance function that considers all measurement to track pairings that satisfy the preliminary gating test. This way, only one measurement is used at each scan to update information pertaining to a particular target (in contrary to all measurements satisfying the gate as in probabilistic data association technique).

2.4 Track Update, Track Initiation

Based on the results of correlation, each of the existing tracks is updated with the correlated measurement. If there is any measurement which

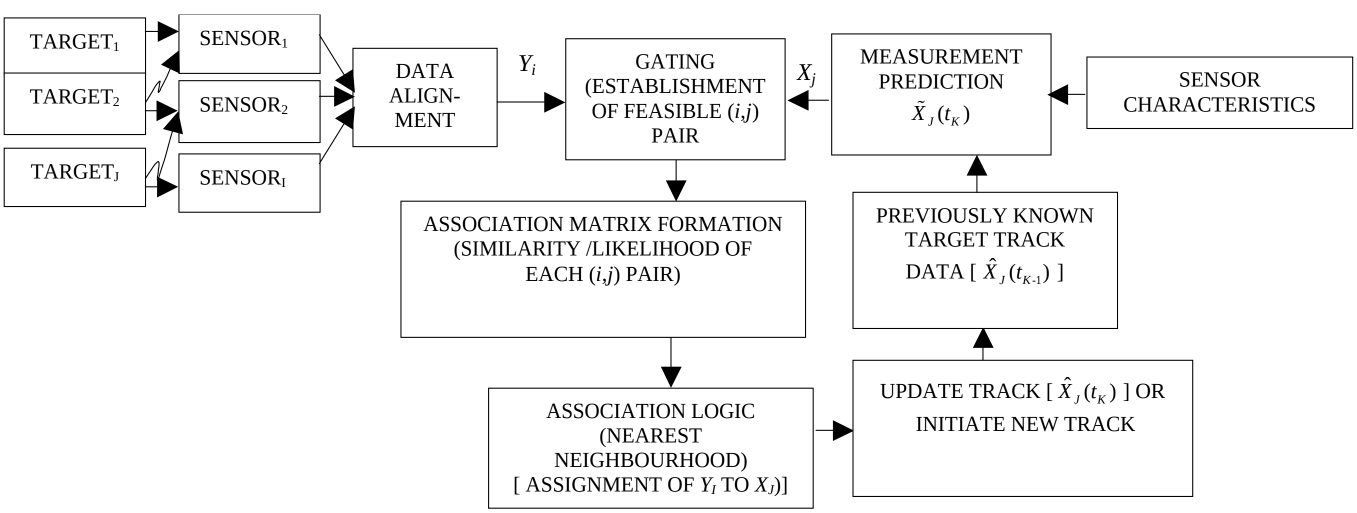


Figure 1. Data association technique in multi-sensor target scenario.

does not satisfy gating test of any of the existing tracks, the measurement is assumed to be generated by a new target. Hence, a new track are initiated based on that measurement. If there are some existing tracks, which do not have any valid measurements associated with them, the track is predicted for the next time interval (without measurement update).

3. NUMERICAL SIMULATION AND RESULTS

The relevance of NN algorithm to a typical test range scenario like ITR can be established by testing and evaluating the algorithm for different possible multi-target scenarios. This is accomplished by testing the algorithm using data from a multiple target-tracking radar. Here, the number of targets tracked by the radar varies at different instants of time. The algorithm does not assume the maximum number of targets tracked by the sensor. In turn, it identifies the number of valid target within the field of view (FOV) of the sensor and estimates state of the targets using the noisy measurement from the sensor. Apart from the NN data association algorithm, the algorithm uses a Kalman filter for estimating the target state. The estimator uses second-order kinematics in Cartesian coordinates for the target model.

The values assumed for the different design parameters of NN algorithm are as given in Table 1. With these parameter values, the algorithm has been tested for two different process noise levels, as mentioned above.

The track results of the algorithm for noise standard deviation of 5 m, 50 m, and 5 m in *x*, *y* and *z* directions, respectively are shown in Figs 2(a)-2(c), and for noise standard deviation of 5 m, 50 m, and 10 m in *x*-, *y*- and *z*-directions, respectively are shown in Figs 3(a)-3(c).

It is seen from the track data of the multi-target tracking (MTT) radar that the elevation measurement is very noisy and that has been reflected in noisy altitude measurement data. Although the estimation results in *x* and *y* positions are satisfactorily,

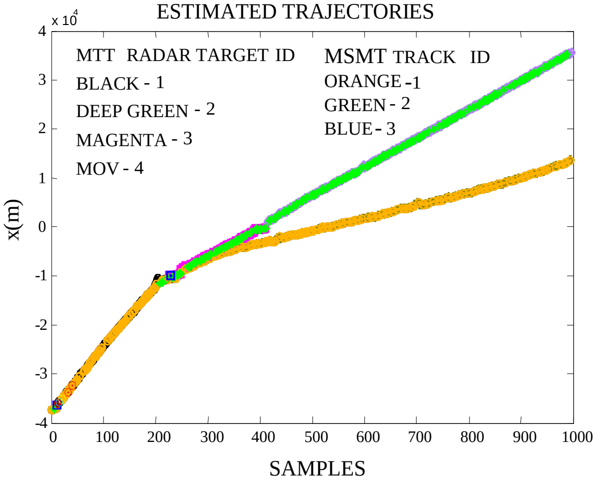
Table 1. Design parameters for NN algorithm

Distance threshold	100 m
Redundant threshold	100 m
Prune threshold	0
Chi square threshold	25
No. of samples	1000
Kalman filter model for target state estimation	Constant velocity model with additive white gaussian noised in acceleration
Process noise standard deviation	10 m^2/s^4 and 100 m^2/s^4 in two different cases of the study
Measurement noise standard deviation	5 m in *x*-direction, 50 m in *y*-direction, and 5 m and 10 m in *z*-direction

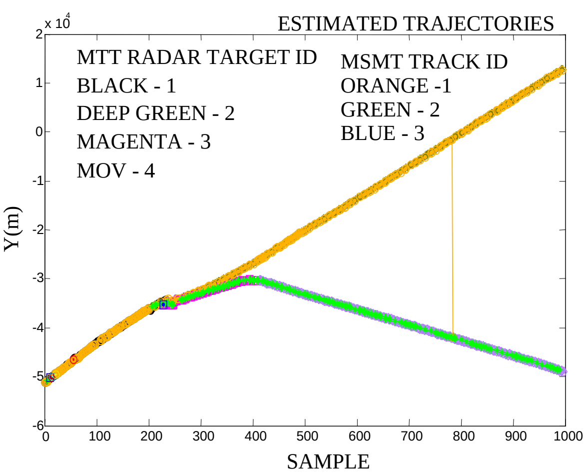
the noisy altitude measurement results in poor performance of altitude estimation. Moreover, the noise standard deviation for the sensor plays a major role in gating performance (by computing the volume around the existing track within which the measurement in the future scans is likely to be). Figure 3 brings out that the larger noise standard deviation assumed in this case results in a erroneous association result at one instant (apparent from the track switching between two targets near sample no. 790).

4. CONCLUSIONS

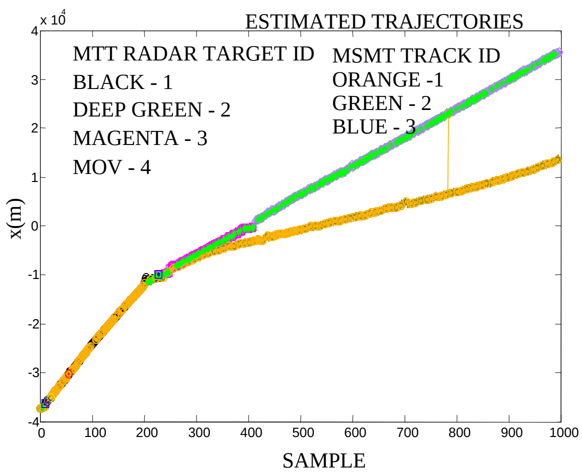
The NN-based data association and target tracking algorithm has been presented and the performance of the algorithm has been established using multiple-target tack data from a radar. The results show that by judicious choice of error variances, the algorithm performs satisfactorily to estimate the kinematic state of all the targets during the flight trials of multiple targets. Since the algorithm utilises track-oriented approach, the information regarding the number of targets present in the scenario is not required for execution of the algorithm. Exhaustive sensitivity studies have been carried out for the adopted algorithm and the results show that the algorithm can perform unambiguously even in the presence of false alarm and for very closely-spaced targets.



(a)

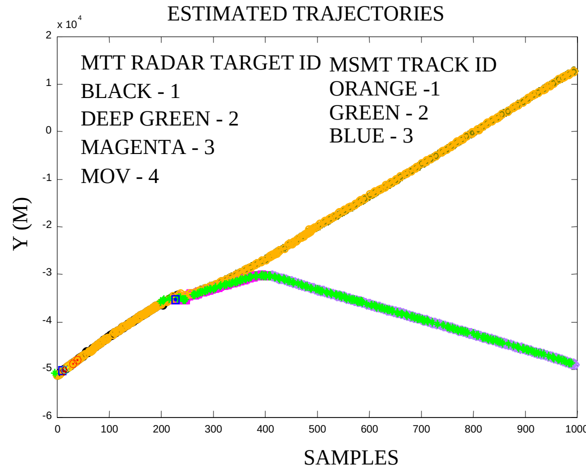


(b)

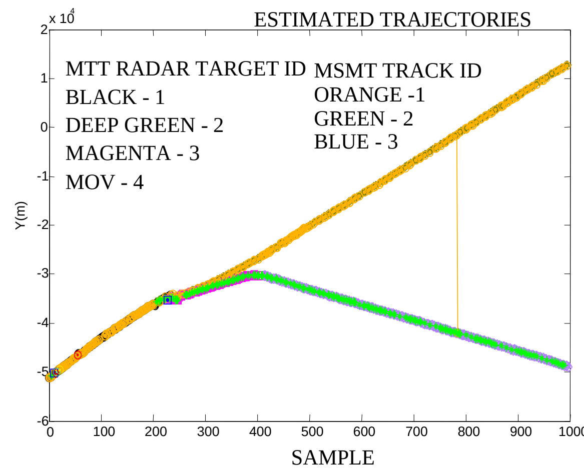


(c)

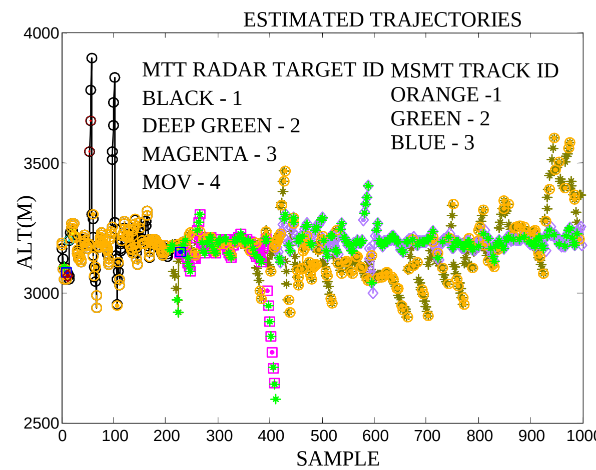
Figures 2(a)-2(c) Track results of the algorithm for noise SD of 5 m, 50 m, and 5 m in x-, y-, and z-directions, respectively.



(a)



(b)



(c)

Figures 3(a)-3(c) Track results of the algorithm for noise SD of 5 m, 50 m, and 10 m in *x*-, *y*- and *z*-directions, respectively.

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