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A Study of a Target Tracking Algorithm Using Global Nearest Neighbor Approach[1]

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Abstract: *This paper compares two algorithms for Multiple Target Tracking (MTT), using Global Nearest Neighbor (GNN) and Suboptimal Nearest Neighbor (SNN) approach respectively. For both algorithms the observations are divided in clusters to reduce computational efforts. For each cluster the assignment problem is solved by using Munkres algorithm or according SNN rules. Results reveal that in some cases the GNN approach gives better solution than SNN approach. The computational time, needed for assignment problem solution using Munkres algorithm is studied and results prove that it is suitable for real time implementations.*

Key words: *Multiple Target Tracking (MTT), Data association, Global Nearest Neighbor (GNN), Suboptimal Nearest Neighbor (SNN), Assignment problem, Munkres algorithm.*

INTRODUCTION

A main function of each radar surveillance system is the target tracking. The basic part of this problem is the process of data association. Most data association methods require a measure of probability in order to evaluate alternative hypotheses. The basic Global Nearest Neighbor (GNN) approach attempts to find and to propagate the single most likely hypothesis at each scan.

In a cluttered environment, the received measurements may not all arise from the real targets. Some of them may be from clutter or false alarm. As a result, there always exist ambiguities in the association between the previous known targets and measurements. Assigning wrong measurements to tracks often results in lost tracks and track breaks. Moreover, clutter can produce false tracks, and if the clutter density is sufficiently large, the resulting number of false tracks can overwhelm the available computational resources of the MTT systems, as well as degrade the overall picture of the environment. For these reasons, techniques dealing with data association have received much attention in MTT research [3, 4].

There are many data association techniques used in MTT systems ranging from the simpler nearest-neighbor approaches to the very complex multiple hypothesis tracker (MHT). The simpler techniques are commonly used in MTT systems, but their performance degrades in clutter. The more complex MHT provides improved performance, but it is difficult to implement and in clutter environments a large number of hypotheses may have to be maintained, which requires extensive computational resources. Because of these difficulties, some other algorithms having smaller computational requirements were developed [8, 2].

The problem of correct data association is difficult to be resolved in dense target environment. In these cases there are clusters with multiple targets and received measurements. There often have ambiguities. Global Nearest Neighbor approach gives an optimal solution. Recently the increased computational power of the computers allows using this approach in real time implementations.

The goal of this paper is to compare two MTT algorithms in which data association is based on SNN and GNN approaches respectively and to study the elapsed time needed for assignment problem solution.

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PROBLEM FORMULATION

The track updating process typically begins with a procedure that is used to choose the best *observation to track* association. This procedure is known as data correlation and is conventionally comprised of two steps called *gating* and *association* [3, 4].

Gating:

Gating is a coarse test for eliminating unlikely observation-to-track pairing. A gate is formed around the predicted position. All measurements that satisfy the gating relationship fall within the gate and are considered for track update. The manner in which the observations are actually chosen to update the track depends on the data association method but most data association methods utilize gating in order to reduce later computation.

The use of Kalman filtering, with the associated covariance matrix, is assumed. At scan $k-1$, the filter evaluates the prediction $\hat{x}_i(k \mid k-1)$ of the state vector of the i^{-th} track. The measurement at scan k is

$$y_j(k) = H\, x_i(k) + v(k), \tag{1}$$

where H is the measurement matrix and $v(k)$ is zero-mean, white Gaussian measurement noise with covariance matrix R. The vector difference between measured and predicted quantities,

$$\tilde{y}_{ij}(k) = y_j(k) - H\hat{x}_i(k \mid k-1), \tag{2}$$

is defined to be residual vector with residual covariance matrix $S = HPH^T + R$, where P is the state prediction covariance matrix. The time subscripts k will be dropped for notational convenience. Assume that the measurement vector size is M. Defining d_{ij}^2 to be the norm of the residual (or innovation) vector,

$$d_{ij}^2 = \tilde{y}_{ij}^T\ S^{-1}\tilde{y}_{ij}, \tag{3}$$

the M-dimensional Gaussian probability density for the residual is

$$g_{ij}(\tilde{y}) = \frac{e^{-\frac{d_{ij}^2}{2}}}{(2\pi)^{M/2}\sqrt{|S_i|}}, \tag{4}$$

where $|S_i|$ is determinant of S_i.

Define a threshold constant for gate G such that correlation is allowed if the following relationship is satisfied by the norm $\left(d_{ij}^2\right)$ of the residual vector

$$d_{ij}^2 = \tilde{y}_{ij}^T\ S_i^{-1}\ \tilde{y}_{ij} < G \tag{5}$$

The quantity d_{ij}^2 is the sum of the squares of M independent Gaussian random variables with zero means and unit standard deviations. For that reason d_{ij}^2 will have χ_M^2 distribution for correct observation-to-track pairings with M degrees of freedom and allowable probability $P = 1 - P_d$ of a valid observation falling outside the gate, where P_d is the probability for correct detection. The threshold constant G can be defined from the table of the chi-square (χ_M^2) distribution with M degrees of freedom and allowable probability of a valid observation falling outside the gate [1].

Data association:

In a dense target environment additional logic is required when an observation falls within the gates of multiple target tracks or when multiple observations fall within the gate of a target track. The optimal assignment minimizes a total distance function which is the sum of the distances for all the individual assignments. Thus it is first necessary to define a distance measure from the predicted positions of track i to observation j. This quantity is termed a normalized or statistical distance function (actually the squared distance). There are several different ways of defining it. One convenient definition is presented in [3]. The basic goal is to choose assignments that maximize the g_{ij} terms. By taking a logarithm of (4) (for better numerical stability to avoid floating point overflow [5]) it is seen that maximization of g_{ij} is equivalent to minimization of the quantity:

$$d_{G_{ij}}^2 = d_{ij}^2 + \ln|S_i| \ . \tag{6}$$

Assuming the same measurement dimension M for all observations, the quantity $d_{G_{ij}}^2 = d_{ij}^2 + \ln|S_i|$ is a convenient distance function for use in the problem of assigning observations to tracks.

Data association takes the output of the gating algorithm and makes final measurement-to-track associations [5]. When a single measurement is gated to a single track, an assignment can be immediately made. However for closely spaced targets, it is more likely that conflict situations will arise. Conflict situations arise when multiple measurements fall within a single gate, or when a single measurement falls within the gates of more than one track. The data association algorithm attempts to resolve these conflicts using probabilistic methods. The simplest is the so-called suboptimal nearest-neighbor (SNN) approach. The SNN assignment algorithm assigns observations to existing tracks minimizing some distance criterion. The SNN looks through the gated measurements and chooses the measurement with minimum distance d_{ij}^2 with the considered track.

An example of complex conflict situation is presented on fig.1.

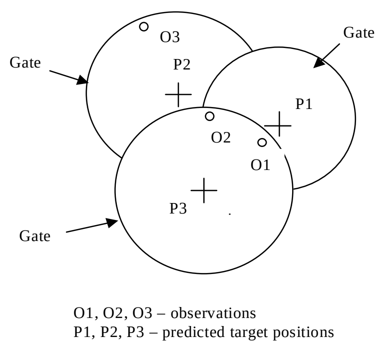

Fig.1 Example of a complex conflict situation

The predicted values define the centre of the gate region. The measurement O2 falls in the gates of the three tracks. In such complex situation the SNN approach could give wrong assignment solution and to lead to missed detection for some track.

ALGORITHM DESCRIPTIONS

We assume the existence of a set of n tracks at the time a new observation or set of observations is received. These observations may be used for updating the existing tracks or for initiating new tracks. Suppose that m measurements are received at time index k. In a cluttered environment, m does not necessarily equal n and it may be difficult to distinguish whether a measurement originated from a target or from clutter. A validated measurement is one which is either inside or on the boundary of the validation gate of a target. Mathematically, a validation gate is defined by equations (5).

The choice of G has to ensure that the correct measurements will lie within the gate with the specified probability. The inequality given in (5) is a validation test. On the base of the validation test the cost matrix C for assignment problem solution is defined.

$$[C_{ij}] = \begin{array}{c} \overbrace{\begin{array}{ccccc} 1 & 2 & 3 & \ldots & m \end{array}}^{j} \\ \begin{bmatrix} c_{11} & c_{12} & c_{13} & : & c_{1m} \\ c_{21} & c_{22} & c_{23} & : & c_{2m} \\ : & : & : & : & : \\ c_{n1} & c_{n2} & c_{n3} & : & c_{nm} \end{bmatrix} \end{array} \left.\begin{array}{c} 1 \\ 2 \\ : \\ n \end{array}\right\} i$$

The elements of the cost matrix c_{ij} have the following values:

$$c_{ij} = \begin{cases} 100 & \textit{if measurement } j \textit{ IS NOT in the gate of track } i \\ d_{ij}^2 & \textit{if measurement } j \textit{ is IN the gate of the track } i \end{cases}$$

Strictly speaking if measurement j is in the gate of the track i $c_{ij} = d_{ij}^2 + \ln|S_i|$ as is given in (6), but the assignment problem solution is the same if $c_{ij} = d_{ij}^2$ [6].

The desired solution of the assignment (cost) matrix is the one that minimizes the summed total distance. For simple cases the optimal solution can be easily found by enumeration. But the enumeration is too much time consuming in more complicated cases. We choose to solve the assignment problem by realizing the extension of Munkres algorithm, given in [6]. As a result we yield the optimal measurements to tracks association. But it is possible (due to missed detection) that some track to be associated with measurement that is not in the gate of the track. That's why it is necessary to check if the element $c_{ij} < G$ i.e. if measurement j is in the gate of the track i or there is missed detection.

GNN algorithm description:

1. *Receiving data* for current scan.
2. *Clusterisation* – measurements to tracks allocation:

   At the beginning all tracks are clusters. In two nested cycles for all tracks and for all measurements using gating criterion it is defined if some measurement falls in the gate of the given track. When two tracks have common measurement in their gates their clusters are merged in supercluster.
3. *For each cluster:*

   3.1. *Measurements to tracks association*.

   At this stage the elements of the cost matrix for the assignment of the measurements to tracks in the current cluster is defined by equation (6). Solve assignment problem using Munkres algorithm.

   3.2.*Track Filtering.*

   Taking from the Munkres solution the associated measurement for each track state update is performed using extended Kalman filter in the frame of Interacting Multiple Model (IMM) approach.
4. *Track Initiation***.**

   Measurements, which are not associated with existing tracks, generate new tracks.

SNN algorithm description:

The SNN algorithm consists of the same steps, but point

3.1. *Measurements to tracks association* is different and consists of the following:

3.1.1. Search the assignment matrix for the closest (minimum distance) observation-to-track pair and make the indicated assignment.

3.1.2. Remove the observation-to-track pair identified above from the assignment matrix and repeat 3.1.1. for reduced matrix.

PROGRAM REALIZATION AND RESULTS

The algorithms described above are realized in Visual C++ (ver.6) and work under Windows'98 on PC with 1.4 GHz. The C++ function for assignment problem solution uses an extension of the Munkres algorithm [6]. This function is studied individually on different computers by different problem sizes (the size of the cost matrix). The elapsed times for the tests are presented in Table 1.

Table 1: Time in seconds for assignment problem solution using Munkres algorithm

Problem size / *PC characteristics:*	*10 x 10*	*50 x 50*	*100 x 100*	*150 x 150*	*200 x 200*
Pentium 133 MHz	0.06	0.17	0.98	4.78	8.30
AMD XP Palomino 1.4GHz	*less than* 0.001	*less than* 0.001	0.05	0.33	0.66

Some of the studied problems are larger than typical real time target tracking cases, but it is evident that such refined algorithms can be used for more complex situations by more sophisticated approaches [9].

For specific scenario with two maneuvering closed spaced targets given in [7] the results prove better solution of GNN algorithm than SNN. Fig. 2 illustrates data association during maneuvering. Predicted values are presented by crosses.

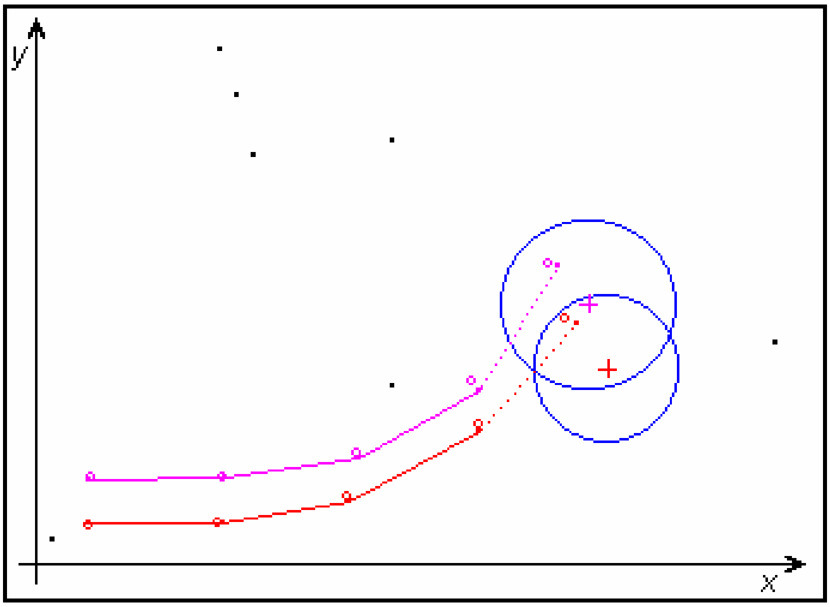

Fig.2: Data association during maneuvering using GNN approach

GNN algorithm due to global optimal solution finds appropriate assignments for both tracks. Using SNN algorithm one of the track "steals" the measurement of another thus causes miscorrelation and one of the two tracks is canceled.

CONCLUSIONS AND FUTURE WORK

The comparison of the two target tracking algorithms reveals better performance of GNN approach versus SNN approach. The software program for assignment problem solution using Munkres algorithm is realized in Microsoft Visual C++ (ver.6). This program is studied individually by five test matrices. The elapsed time for problems with dimensions up to 50x50 on PC 1.4 GHz is under 0.001 [sec] and allows real time implementations even for more elaborate algorithms.

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