Performance Evaluation of Tracking Algorithm Incorporating Attribute Data Processing via DSmT[1]

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Abstract* – The main objective of this paper is to investigate the impact of the quality of attribute data source on the performance of a target tracking algorithm. An array of dense scenarios arranged according to the distance between closely spaced targets is studied by different confusion matrices. The used algorithm is Generalized Data Association (GDA-MTT) algorithm for multiple target tracking processing kinematic as well as attribute data. The fusion rule for attribute data is based on Dezert-Smarandache Theory (DSmT). Besides the main goal a comparison is made between the cited above algorithm and an algorithm with Kinematic based only Data Association (KDA-MTT). The measures of performance are evaluated using intensive Monte Carlo simulation.

Keywords: Tracking, data association, estimation, Dezert-Smarandache Theory (DSmT), fusion rules.

1 Introduction

Target tracking of closely spaced targets is a challenging problem. The kinematic information is often insufficient to make correct decision which observation to be associated to some existing track. A new approach presented in [16] describes Generalized Data Association (GDA) algorithm incorporating attribute information. The presented results are encouraging, but it is important to study the algorithm performance for more complex scenarios with more maneuvering targets and different levels of quality of attribute data source. It is important to know the level of quality of the used attribute detection to assure robust target tracking in critical, highly conflicting situations. The goal of this paper is by using Monte Carlo simulation to determine the sufficient level of quality of attribute measurements that for given standard deviations of the kinematic measurements (in our case azimuth and distance) to assure allowable miscorrelations.

2 Problem formulation

Classical target tracking algorithms consist mainly of two basic steps: *data association* to associate proper measurements (usually kinematic measurement $z(k)$) representing either position, distance, angle, velocity, accelerations etc.) with correct targets; *track filtering* to estimates and predict the state of targets once data association has been performed. The first step is very important for the quality of tracking performance since its goal is to associate correctly observations to existing tracks. The data association problem is very difficult to solve in dense multitarget and cluttered environment. To eliminate unlikely (kinematic-based) observation-to-track pairings, the classical validation test [3,7] is carried on the Mahalanobis distance

$$d_j^2(k) = \nu_j'(k) S^{-1} \nu_j(k) \leq \gamma, \tag{1}$$

where

$\nu_j(k) = \hat{z}(k) - z_j(k)$ is the difference between the predicted position $\hat{z}(k)$ and the $j-th$ validated measurement $z_j(k)$, S is the innovation covariance matrix, γ is a threshold constant defined from the table of the chi-square distribution [3]. Once all the validated measurements have been defined for the surveillance region, a clustering procedure defines the clusters of the tracks with shared observations. Further the decision about observation-to-track associations *within the given cluster* with n existed tracks and m received measurements is considered. The Converted Measurement Kalman Filter (CMKF) [5] coupled with a classical Interacting Multiple Model (IMM) for maneuvering target tracking is used to update the targets' state vectors. In the CMKF algorithm the classical linearized conversion is used as the value of validation indicator for unbiased filtering, proposed in [11] $\left(\frac{r\sigma_\theta}{\sigma_r} < 0.4\right)$ is less than 0.01 in our scenario. The GDA-MTT improves data association process by adding attribute measurements (like amplitude information or RCS (radar cross section) [#16-7]), or eventually as in [6], target type decision coupled with confusion matrix to classical kinematic measurements to increase the performance of the MTT system. When attribute data is available, the generalized (kinematic and attribute) likelihood ratios are used to improve the assignment. The GNN approach is used in order to make a decision for data association on integral criterion base. The used GDA approach consists in choosing a set of

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assignments $\{\chi_{ij}\}$ for $i=1,\cdots,n$ and $j=1,\cdots,m$, that assures maximum of the total generalized likelihood ratio sum by solving the classical assignment problem $\min\sum_{i=1}^{n}\sum_{j=1}^{m} a_{ij}\chi_{ij}$,

where

$$a_{ij} = -\log(LR_{gen}(i,j))$$

with

$$LR_{gen}(i,j) = LR_k(i,j)LR_a(i,j),$$

where $LR_k(i,j)$ and $LR_a(i,j)$ are kinematic and attribute likelihood ratios respectively, and

$$\chi_{ij} = \begin{cases} 1 & \text{if measurement } j \text{ is assigned to track } i \\ 0 & \text{otherwise} \end{cases}$$

Or, when the assignment matrix $A=[a_{ij}]$ is constructed its elements a_{ij} take the following values [12]:

$$a_{ij} = \begin{cases} \infty & \text{if } d_{ij}^2 > \gamma \\ -\log(LR_k(i,j)LR_a(i,j)) & \text{if } d_{ij}^2 \le \gamma \end{cases}$$

The solution of the assignment matrix is the one that minimizes the sum of the chosen elements. We solve the assignment problem by realizing the extension of Munkres algorithm, given in [9]. As a result one obtains the optimal measurements to tracks association. Once the optimal assignment is found, i.e. the correct association is available, then standard tracking filter is used depending on the dynamics of the tracking targets.

2.1 Kinematic Likelihood Ratios for GDA

The kinematic likelihood ratios $LR_k(i,j)$ involved into a_{ij} are easy to obtain because they are based on the classical statistical models for spatial distribution of false alarms and for correct measurements [5]. $LR_k(i,j)$ is evaluated as: $LR_k(i,j) = LF_{true}(i,j)/LF_{false}$,

where LF_{true} is the likelihood function that the measurement j originates from a target (track) i and LF_{false} is the likelihood function that the measurement j originates from a false alarm. At any given time k, LF_{true} is defined as

$$LF_{true} = \sum_{l=1}^{r}\mu_l(k)LF_l(k),$$

where r is the number of the models (in our case of two nested models $r=2$ are used for CMKF-IMM, $\mu_l(k)$ is the probability (weight) of the model l for the scan k, $LF_l(k)$ is the likelihood function that the measurement j originates from target (track) i according to the model l, i.e.

$$LF_l(k) = \frac{1}{2\pi\sqrt{|S_l^i(k)|}}e^{-d_l^2(i,j)/2}.$$

LF_{false} is defined as $LF_{false} = P_{fa}/V_c$, where P_{fa} is the false alarm probability and V_c is the resolution cell volume chosen as in [6] as $V_c = \prod_{i=1}^{n_z}\sqrt{12R_{ii}}$. In our case, $n_z = 2$ is the measurement vector size and R_{ii} are sensor error standard deviations for azimuth β and distance D measurements.

2.2.Attribute Likelihood Ratios for GDA

The major difficulty to implement GDA-MTT depends on the correct derivation of coefficients a_{ij}, and more specifically the attribute likelihood ratios $LR_a(i,j)$ for correct association between measurement j and target i based only on attribute information. When attribute data are available and their quality is sufficient, the attribute likelihood ratio helps a lot to improve MTT performance. In our case, the target type information is utilized from RCS attribute measurement through fuzzification interface. A particular confusion matrix is constructed to model the sensor's classification capability.

The approach for deriving $LR_a(i,j)$ within DSmT [10,14,15] is based on relative variations of pignistic probabilities [15] for the target type hypotheses, H_j (j=1 for Fighter, j=2 for Cargo), included in the frame Θ_2 conditioned by the correct assignment. These pignistic probabilities are derived after the fusion between the generalized basic belief assignments of the track's old attribute state history and the new attribute/ID observation, obtained within the particular fusion rule. It is proven that this approach outperforms most of the well known ones for attribute data association. It is defined as :

$$\delta_i(P^*) = \frac{|\Delta_i(P^*|Z) - \Delta_i(P^*|\hat{Z}=T_i)|}{\Delta_i(P^*|\hat{Z}=T_i)} \quad (3)$$

where

$$\begin{cases} \Delta_i(P^*|Z) = \sum_{j=1}^{2}\frac{|P_{T_iZ}^*(H_j) - P_{T_i}^*(H_j)|}{P_{T_i}^*(H_j)} \\ \Delta_i(P^*|Z=T_i) = \sum_{j=1}^{2}\frac{|P_{T_iZ=T_i}^*(H_j) - P_{T_i}^*(H_j)|}{P_{T_i}^*(H_j)} \end{cases}$$

i.e. $\Delta_i(P^*|\hat{Z}=T_i)$ is obtained by forcing the attribute observation mass vector to be the same as the attribute mass vector of the considered real target, i.e. $m_Z(.) = m_{T_i}(.)$. The decision for the right association relies on the minimum of expression (3). Because the generalized likelihood ratio RL_{gen} is looking for the maximum value, the final form of the attribute likelihood ratio is defined to be inverse proportional to the $\delta_i(P^*)$ with i defining the number of the track, i.e. $LR_a(i,j) = 1/\delta_i(P^*)$.

3 Numerical experiments' frame and results

3.1 Experiments' frame

For the experiments we use an extension of the program packet TTLab [13], written in MatLab. This extension takes into account the attribute information. A program-human interface facilitates the changing of the design parameters of the algorithms.
The simulation scenario consists of twenty five air targets (Fighter and Cargo) moving in three groups from North-West to South-East with constant velocity of 170[m/sec]. The stationary sensor is at the origin with T_{scan} = 5 [sec], measurement standard deviations 0.3[deg] and 100[m] for azimuth and range respectively. The headings of the central group are 135[deg] from North and for the left and right groups are 150[deg] and 120[deg] respectively. During the scans from 15th to 17th and from 48th to 50th the targets of the left and right groups perform maneuvers with transversal acceleration 4.4[$m/\sec^2$]. The targets are closely spaced especially in the middle part of their trajectories. The scenario is shown on figure 1.

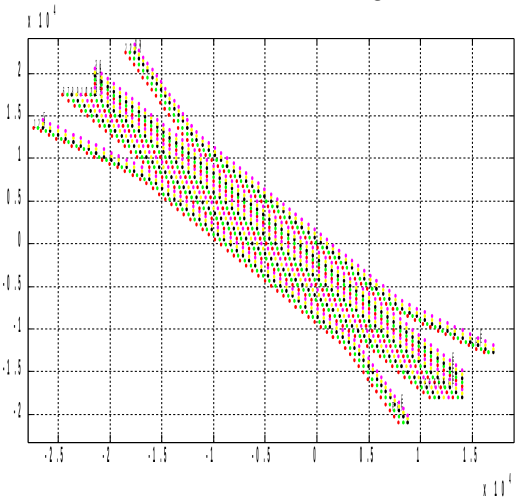

Figure 1 : Multitarget scenario with 25 targets

The typical tracking performances for KDA-MTT and GDA-MTT algorithms are shown on figures 2 and 3 respectively.

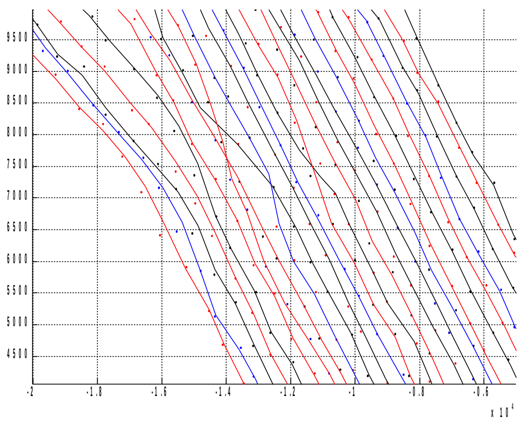

Figure 2 : Typical performance with KDA-MTT

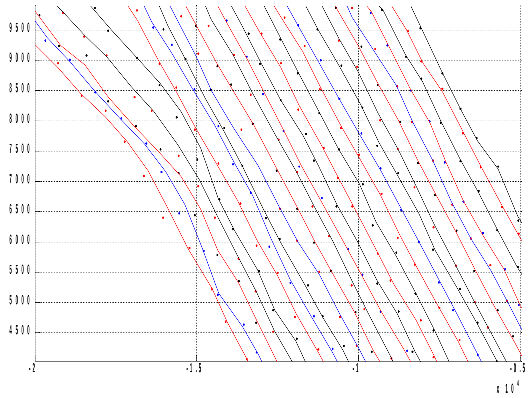

Figure 3 : Typical performance with GDA-MTT

The *Track Purity* performance metrics is used to examine the ratio of the correct associations. Track purity is considered as a ratio of the number of correct observation-to-track associations (in case of detected target) over the total number of all possible associations during the scenario tracking.
Our aim in these experiments is to investigate what level of classifier accuracy we need in a particular scenario with the given separation between closely spaced targets. Recalling that the confusion matrix (CM) specifies the prior accuracy of the classifier we perform consecutive experiments starting with CM corresponding to the highest accuracy and ending with a matrix close to real life.
Beforehand, we have implemented a series of experiments with highest accuracy CM and different separations of the targets starting with prohibited close separation (approximately $d = 1.5\sigma_{res}$; here σ_{res} is residual standard deviation, ranging from 260[m] at the beginning of the trajectory to 155[m])[2]. With these experiments we try to find out the particular target's separation which insures good results in term of tracks' purity metrics.
Besides the algorithm processing attribute data on the base of Proportional Conflict Redistribution Rule number 5 (PCR5) from DSm theory simultaneously the same tracking algorithm is run with the kinematic data processing only.

3.2 Numerical results

We started our experiments with series of runs with different target separation and confusion matrix

$$CM = \begin{bmatrix} 0.995 & 0.005 \\ 0.005 & 0.995 \end{bmatrix}.$$

Hereafter, because of symmetry we will show the first row of the matrix only. All the values in the tables below are averaged over the 50 Monte Carlo runs. At a distance of 300[m] between targets the results are extremely discouraging for both the kinematic only and kinematic and attribute data used (the first row of table 1). There is no surprise because this separation corresponds to less than $1.5\sigma_{res}$. This row stands out with remarkable ratio of 'attribute' to 'kinematic' percents of tracks' purity. In the ‘kinematic’ case less than one tenth of tracks are processed properly while with using the attribute data almost two thirds of targets are not lost. Nevertheless, the results are poor and unacceptable from the practical point of view. In the next rows we increase gradually the distance between targets reaching separation of 600[m]. This distance corresponds to $2.5\sigma_{res}$ and the results are good enough especially for the DSmT based algorithm.

Table 1: `Pd=0.995,    CM(0.995, 0.005)`

Distance [m]	Track purity [%]	
	GDA (PCR5)	KDA
300	57.99	8.65
350	74.47	12.43
400	87.45	21.17
450	**93.24**	**35.47**
500	95.94	56.12
550	96.74	74.74
600	97.76	86.40

The next step is to choose this medium separation size which ensures highly acceptable results. We take the distance of 450[m] because it is in the middle of the table and its results are very close to that of larger distances. Now we start our runs with confusion matrix (0.995;0.005) corresponding to highest accuracy and gradually change its elements to more realistic values (table 2). In this table the tracks’ purity data for ‘kinematic’ only algorithm are omitted because they do not depend on confusion matrix values. Now we choose the threshold of 85% for tracks’ purity value above which could be said that the results are satisfying enough. Actually, the choice of threshold is a matter of an expert assessment and strongly depends on the particular implementation.It can be seen from the table that the last row stepping from the top with tracks’ purity value above the chosen threshold is the row with CM with elements (0.96;0.04). So that, if our task is to track targets separated at normalized distance approximately $1.5\sigma_{res}$ to $3\sigma_{res}$ we have to ensure classifier with mentioned above confusion matrix. As a comparison could be remained the value of tracks’ purity ratio for the ‘kinematic’ algorithm for this separation – **35.47%.**

Table 2 Track purity results with different confusion matrices for scenario with distance 450[m]

Distance [m] 450		
Confusion Matrix		**Track Purity**
0.995	0.005	93.24
0.99	0.01	91.51
0.98	0.02	89.53
0.97	0.03	86.83
0.96	**0.04**	**85.26**
0.95	0.05	82.48
0.94	0.06	79.41
0.93	0.07	75.38
0.92	0.08	75.25
0.91	0.09	74.27
0.90	0.10	70.69

Some additional experiments have been performed with continuing change of the elements of CM worsening the classifier accuracy and trying to answer the question how looks the CM which do not influence the value of tracks’ purity ratio, i.e. when the ‘attribute’ algorithm gives the same results as ‘kinematic’ one for the chosen separation. The results can be seen in table 3. Even for the values of elements of CM close to the natural limit values of (0.5;0.5) the investigated ratio remains slightly better (the last row of table 3) than that of ‘kinematic’ algorithm.

Table 3 : Distance =450[m] , PCR5 algorithm

Distance [m] 450		
Confusion Matrix		**Track Purity**
0.995	0.005	93.24
0.95	0.05	82.48
0.90	0.10	70.69
0.80	0.20	52.04
0.70	0.30	46.90
0.60	0.40	43.01
0.55	0.45	42.20

After correct association is made the classical IMM Kalman filtering algorithm is used to diminish position errors. The figures 4 and 5 shows the errors along axes X and Y with and without filtering. It can be seen the effect of significant reduction of the sensor errors after filtering. On figure 4 is presented the result of more precise model 1, and on figure 2 is the result of model 2 with bigger values for errors.

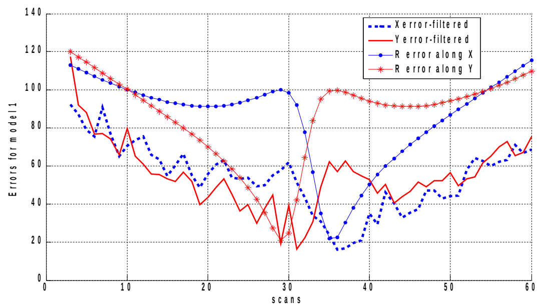

Figure 4 : Monte Carlo estimation of errors along axes x and y for model 1

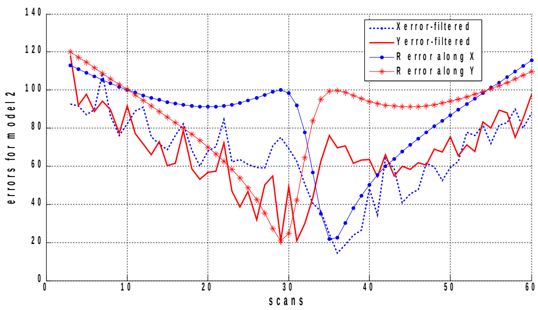

Figure 5 : Monte Carlo estimation of errors along axes x and y for model 2

On figure 6 the result for distance errors for the two models is presented. It can be seen that the errors for the more precise first model the errors are lower.

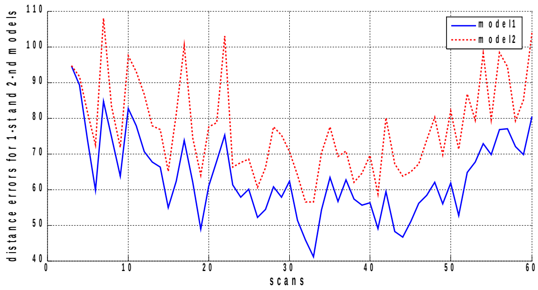

Figure 6 : Monte Carlo estimation of distance errors for first and second models

Conclusions

In this paper a series of experiments have been performed aiming to investigate the influence of some circumstances and values of some particular parameters on performance capability of multiple target tracking algorithm processing both kinematic and attribute data. The algorithm is based on Global Nearest Neighbour-like approach and uses Munkres algorithm to resolve the generalized association matrix. The principles of Dezert-Smarandache theory of plausible and paradoxical reasoning to utilize attribute data are applied. The results show that even in dense target scenarios and realistic accuracy of attribute data classifier the algorithm performance meets requirements concerning its practical implementation. Beside this inference, the results once more underline the advantage of used algorithm utilizing both kinematic and attribute data over that one working with kinematic data only.

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