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Performance evaluation of a tracking algorithm including attribute data

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Abstract: *The main objective of this work 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 algorithm for Multiple Target Tracking (GDA-MTT) 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.*

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14.1 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 [15] describes a 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 attribute detection used 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 overcome allowable miscorrelations.

14.2 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

$$d_j^2(k) = v_j'(k) S^{-1} v_j(k) \leq \gamma, \tag{14.1}$$

where $v_j(k) = \hat{z}(k) - z_j(k)$ 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 existing tracks and m received measurements is considered. The Converted Measurement Kalman Filter (CMKF) [5] coupled with a classical Interacting Multiple Models (IMM) [1, 4, 8] for maneuvering target tracking is used to update the targets' state vectors.

When CMKF is used, one advantage and one drawback arise. Receiving measurements in (x, y) coordinates allows us to continue our tracking with a simple Linear Kalman Filter (KF) instead of more complicated Extended Kalman Filter (EKF). The more sophisticated calculation of the measurement matrix in EKF is replaced with a more sophisticated calculation of converted measurement covariance at each recursion of the filter. The drawback is that CMKF accuracy strongly depends not only on the original measurement accuracy but on scenario geometry, as well. In some cases the mean of the errors is significant and unbiased compensation is needed. In [11], a limit of validity is derived when classical linearized conversion in CMKF is used - ($\frac{r\sigma_\theta^2}{\sigma_r} < 0.4$), where σ_θ and σ_r are the standard deviations for azimuth and distance measurements respectively. The quantity from the left-hand side in our scenarios is most often less than 0.01 and, hence, the validity limit is fully satisfied. The GDA-MTT improves data association process by adding attribute measurements, like amplitude information or RCS (radar cross section) [16], or eventually [6], target type decision coupled with the confusion matrix to classical kinematic measurements in order 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 Global Nearest Neighbor (GNN) approach is used in order to make a decision for data association on an integral criterion base. The used GDA approach consists in choosing a set of assignments $\{\chi_{ij}\}$ for $i = 1, ..., n$ and $j = 1, ..., m$, 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

$$LR_{gen}(i,j) = LR_k(i,j)LR_a(i,j). \tag{14.2}$$

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

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

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

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

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, the standard tracking filter is used depending on the dynamics of the tracked targets.

14.2.1 Kinematic likelihood ratios for GDA

The kinematic likelihood ratios $LR_k(i,j)$ involved into a_{ij} are easily 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 $LF_{true}(i,j)$ 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 used for CMKF-IMM (in our case of two nested models $r = 2$). $\mu_l(k)$ 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.

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

LF_{false} is defined as $LF_{false} = \frac{P_{fa}}{V_c}$, where P_{fa} is the false alarm probability and V_c is the resolution cell volume chosen 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.

14.2.2 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 a 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 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 :

$$\delta_i(P^*) \triangleq \frac{\left|\Delta_i(P^*|Z) - \Delta_i(P^*|\hat{Z} = T_i)\right|}{\Delta_i(P^*|\hat{Z} = T_i)}, \tag{14.3}$$

where

$$\begin{cases} \Delta_i(P^*|Z) = \sum_{j=1}^{2} \frac{\left|P^*_{T_i Z}(H_j) - P^*_{T_i}(H_j)\right|}{P^*_{T_i}(H_j)} \\ \Delta_i(P^*|Z = T_i) = \sum_{j=1}^{2} \frac{\left|P^*_{T_i Z = T i}(H_j) - P^*_{T_i}(H_j)\right|}{P^*_{T_i}(H_j)} \end{cases}$$

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 (14.3). Because the generalized likelihood ratio LR_{gen} is looking for the maximum value, the final form of the attribute likelihood ratio is defined to be inversely proportional to the $\delta_i(P^*)$ with i defining the number of the track, i.e. $LR_a(i, j) = 1/\delta_i(P^*)$.

14.3 Scenario of simulations and results

14.3.1 Scenario of simulations

For the simulations, we use an extension of the program package TTLab developed under MATLAB$^{\text{TM}}$ for target tracking [13]. This extension takes into account the attribute information. A friendly human-computer interface facilitates the changes 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 14.1.

The typical tracking performances for KDA-MTT and GDA-MTT algorithms are shown on figures 14.2 and 14.3 respectively. The Track Purity performance metrics is used to examine the fraction/percent of the correct associations. Track purity is defined as a ratio of the number of correct observation-to-track associations to total number of all possible associations during the process of tracking. Track purity metrics concerns every single target and could be averaged over all targets in the scenario as well as over all Monte Carlo runs.

Our aim in these simulations is to investigate what level of classifier accuracy we need in a particular scenario with the given separation between the closely spaced targets. We have performed consecutive simulations starting with a confusion matrix (CM) corresponding to the highest (prior) accuracy and ending with a matrix close

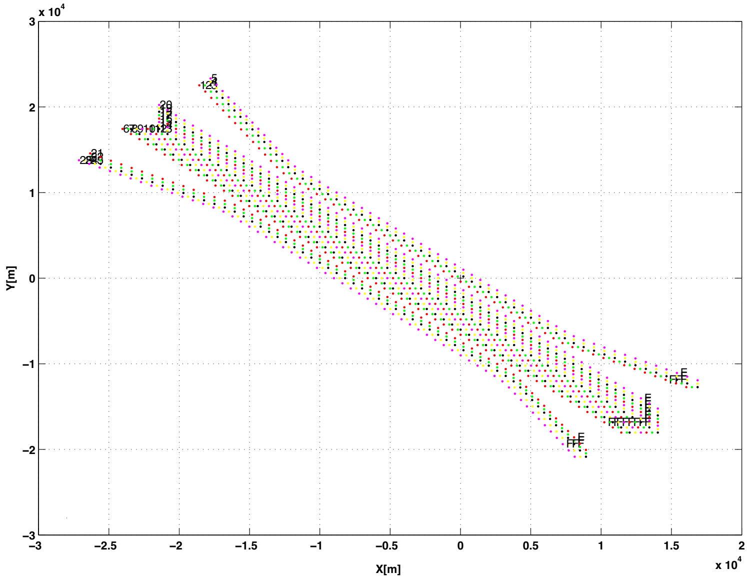

Figure 14.1: Multitarget scenario with 25 targets.

to what is expected in pratice with common classifiers.

Before this, we did several simulations with highest accuracy CM and different separations of the targets starting with prohibitively close separation (approximately $d = 1.5\ \sigma_{resid}$; here σ_{resid} is the residual standard deviation, ranging from 260 m at the beginning of the trajectory to 155 m) [2]. From these simulations, we try to find out the particular target's separation which insures good results in term of tracks' purity metrics.

14.3.2 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 next tables are averaged over the 50 Monte Carlo runs. At a

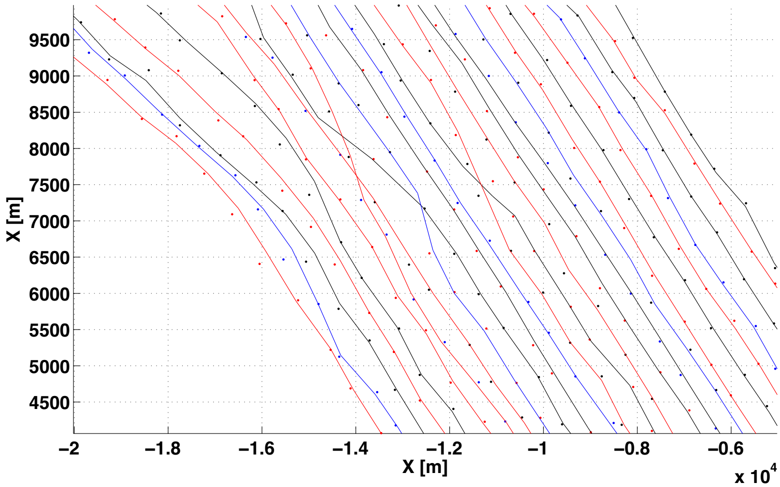

Figure 14.2: Typical performance with KDA-MTT.

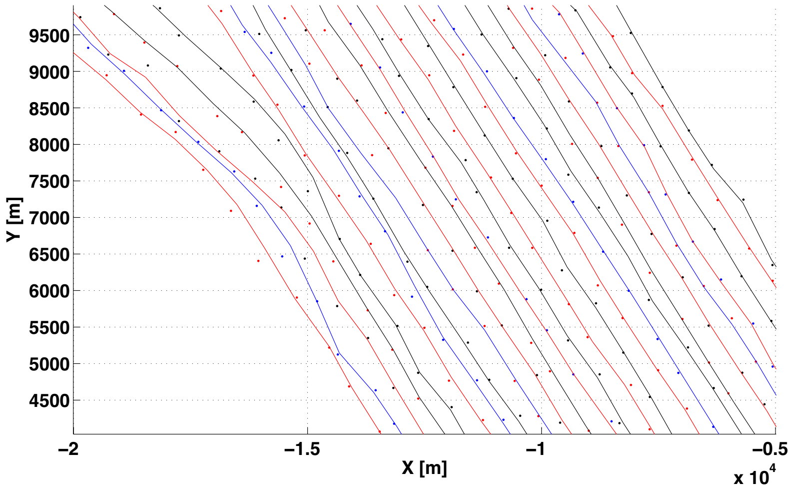

Figure 14.3: Typical performance with GDA-MTT.

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 the Table 14.1). There is no surprise because this separation corresponds to less than 1.5 σ_{resid}. 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 ot the table, we have increased gradually the distance between the targets until reaching a separation of 600 m. This distance corresponds to 2.5 σ_{resid} and the results are good enough especially for the DSmT based algorithm.

Distance in 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

Table 14.1: $P_d = 0.995$, $CM(0.995, 0.005)$.

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 according to the Table 14.2. In this table, the tracks' purity for the pure data kinematic-based algorithm are omitted because they do not depend on the confusion matrix values. Then we have chosen the threshold of 85% for tracks' purity value since this threshold provides results which are considered as 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 14.2 that the last row from the top with tracks' purity value above the chosen threshold is the row with CM(0.96;0.04). So that, if our task is to track targets separated at normalized distance approximately $1.5\sigma_{resid}$ to $3\sigma_{resid}$, we have to ensure a classifier with mentioned above confusion matrix. We recall that the value of the tracks' purity ratio for the pure data kinematic-based algorithm for this separation is only 35.47%.

More simulations have been performed by degrading the quality of the classifier/CM for trying to find the values of CM which does not influence the value of tracks' purity ratio, i.e. when the 'attribute' algorithm gives the same results as

Distance $d = 450\ m$		
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

Table 14.2: Track purity with different CM for a scenario with $d = 450\ m$.

'kinematic' one for the chosen targets separation. The results we have obtained are given in Table 14.3.

Distance $d = 450\ m$		
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

Table 14.3: Distance = 450 m, PCR5 algorithm.

We can see that even for the values of elements of CM close to the probability mass limit values of (0.5;0.5) the investigated ratio remains slightly better (the last row of table 14.3) than that of 'kinematic' algorithm.

Once the data association is made, the classical IMM Kalman filtering algorithm is used for target state estimation and to reduce position errors. The figures 14.4 and 14.5 show the errors along axes X and Y with and without filtering. It can be seen a significant reduction of the sensor errors after filtering. The figure 14.4 shows the result of the more precise model (model 1), and in the figure 14.2 the result of model 2 with bigger values for errors is presented. The figure 14.6 shows the result for distance errors for the two models. We can verify that we naturally obtain lower errors when using the most precise model.

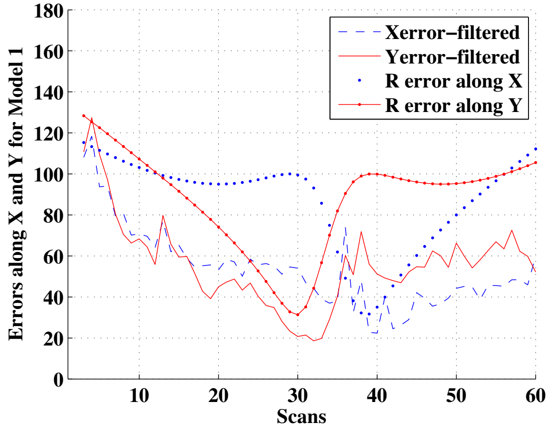

Figure 14.4: Monte Carlo estimation of errors allong axes x and y for model 1.

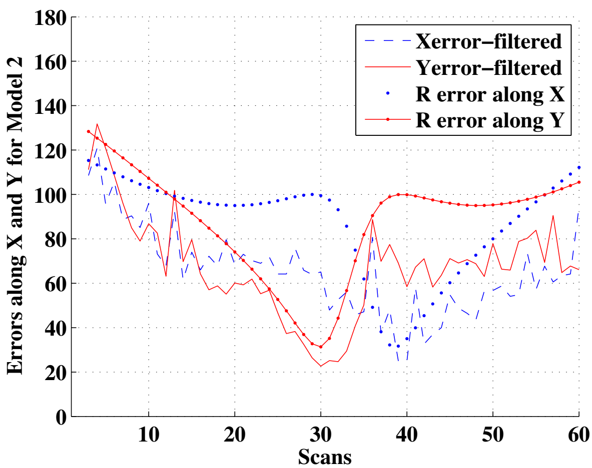

Figure 14.5: Monte Carlo estimation of errors allong axes x and y for model 2.

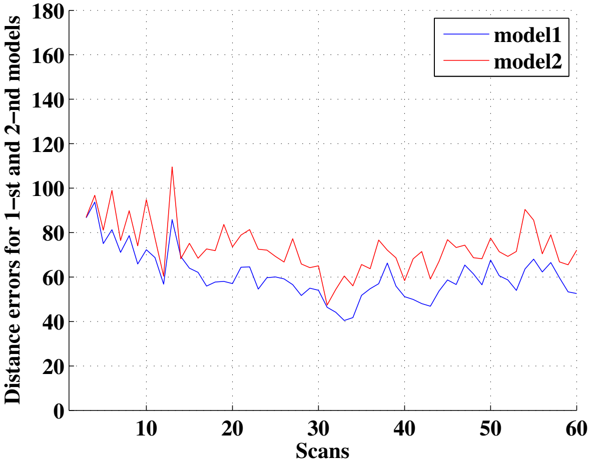

Figure 14.6: Monte Carlo estimation of distance errors for first and second models.

14.4 Conclusions

In this work, we have proposed and evaluated a multiple target tracking algorithm called GDA-MTT dealing with both kinematic and atrribute data. GDA-MTT is based on a global nearest neighbour alike approach which uses Munkres algorithm to solve the generalized data association problem. The PCR5 combination rule developed in Dezert-Smarandache Theory has been used for managing efficiently attribute data which allows to improve substantially the tracking performances. Our simulation results show that, even in dense target scenarios and realistic accuracy of attribute data classifier, the GDA-MTT algorithm's performance meets requirements concerning its practical implementation. Our results highlight the advantage of using a tracking algorithm exploiting both kinematic and attribute data over a classical tracking approach based only on kinematic data.

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