Multitarget Tracking Performance based on the Quality Assessment of Data Association

Jean Dezert
The French Aerospace Lab (ONERA)
BP80100, FR-91123, Palaiseau, France.
E-mail: jean.dezert@onera.fr

Albena Tchamova
Institute of I&C Tech.
Bulgarian Acad. of Sci., Sofia, Bulgaria.
E-mail: tchamova@bas.bg

Pavlina Konstantinova
European Polytechnical University
Pernik, Bulgaria.
E-mail: pavlina.konstantinova@gmail.com

***Abstract*—The main objective of this paper is to present, to apply, and to test the effectiveness of the new method, based on belief functions, proposed by Dezert et al. in order to evaluate the quality of the individual association pairings provided in the classical optimal data association solution for improving the performances of multitarget tracking systems in clutter, when some of the association decisions given in the optimal assignment solution are unreliable and doubtful and lead to potentially critical mistake. This evaluation is based on a Monte Carlo simulation for particular difficult maneuvering and non-maneuvering MTT problems in clutter. A comparison with the results obtained on the base of Kinematic only Data Association and Generalized Data Association is made.**

Keywords: Data association, Belief Functions, PCR6 fusion rule, multitarget tracking.

I. Introduction

Data association (DA) is a fundamental and central problem in up-to-date multitarget tracking (MTT) systems ([1] and [2]). It entails selecting the most trustable associations between uncertain sensor's measurements and existing targets at a given time. In the presence of dense MTT environment, with false alarms and sensors detection probability less than unity, the problem of DA becomes more complex, because it should contend with many possibilities of pairings, some of which are in practice very doubtful, unreliable, and could lead to critical association mistakes in overall tracking process. To avoid such cases, sometimes it is better to wait for a new measurements during the next scan, instead of taking a hard DA decision, which actually is not always unique.

Several methods have been devised over the years, in order to resolve properly DA problem. They are originating from different models. Some rely on the established reward matrix based on Kinematic only Data Association (KDA) and on a probabilistic framework [3], [4]. Some other studies are based on Belief Functions (BF) ([5]- [9]), motivating the incorporation of the advanced concepts for Generalized Data Association (GDA) ([6]- [8]), where a particular target's attribute is introduced into the association logic in order to compensate the complicated cluttered cases, when kinematics data are insufficient for adequate decision making. Dezert-Smarandache Theory (DSmT) of plausible and paradoxical reasoning [8] is used to model and to process the utilized attribute data. Although interesting and approved, all these methods currently developed are limited to the following aspect - all of them solve the optimal DA problem and use all optimal observations-to-tracks pairings, selected in the first best DA solution to update tracks, even if some of them have poor quality. In consequence the overall tracking performance could be degraded substantially. In order to deal with this case the most recent method to evaluate the Quality Assessment of Data Association (QADA) encountered in multiple target tracking applications in a mono-criterion context is proposed by Dezert and Benameur [10]. It is extended in [11] for the multi-criteria context. This novel method assumes the reward matrix is known, regardless of the manner in which it is obtained by the user. It is based on BF for achieving the quality of pairings (interpreted as a confidence score) belonging to the optimal data assignment solution based on its consistency (stability) with respect to all the second best solutions, provided by a chosen algorithm.

This paper is an extension of our preliminary study on the effect of applying QADA method in MTT presented in [17]. The main purpose of our paper is to assess the efficiency of QADA method in a critical, conflicting MTT situation. The evaluation is based on a Monte Carlo simulation for particular difficult maneuvering and non-maneuvering MTT problems in clutter. The QADA based MTT performance is compared with the results, obtained for KDA and GDA based MTT, concerning the same scenarios. The paper is organised as follows. In order to achieve a good readability of the paper, we recall in section II the data association problem within the MTT context, and in a section III the details of the new method, proposed by Dezert et al. [10] for quality assessment of pairings, chosen in the optimal DA solution. In section IV we discuss and propose the way in which Kalman filtering could be affected in order to reflect the knowledge we have obtained on the base of QADA method. Two simulation MTT scenarios (with non-maneuvering and maneuvering targets) are presented and the results, obtained on the base of QADA-, KDA-, and GDA based MTT are discussed. Conclusions are made in Section VI.

II. Data Association problem in MTT context

The DA problem consists in finding the global optimal assignments of targets $T_i, i = 1, ..., m$ to some measurements $\mathbf{z}_j, j = 1, ..., n$ at a given time k by maximizing the overall gain in such a way, that no more than one target is assigned to a measurement, and reciprocally.

The $m \times n$ reward (gain/painoff) matrix $\mathbf{\Omega} = [\omega(i,j)]$ is defined by its elements $\omega(i,j) > 0$, representing the gain of the association of target T_i with the measurement $\mathbf{z}_j$. These values are usually homogeneous to the likelihood ratios. In our case $\omega(i,j)$ represents the normalized distances between the measurement Z_j and target T_i : $d^2(i,j) \triangleq (\mathbf{z}_j(k) - \hat{\mathbf{z}}_i(k|k-1))'\mathbf{S}^{-1}(k)(\mathbf{z}_j(k) - \hat{\mathbf{z}}_i(k|k-1)) \leq \gamma$ computed from the measurement $\mathbf{z}_j(k)$ and its prediction $\hat{\mathbf{z}}_i(k|k-1)$ computed by the tracker of target i (see [2] for details), and the inverse of the covariance matrix $\mathbf{S}(k)$ of the innovation computed by the tracking filter. In this case the DA problem consists in finding the best assignment, minimizing the overall cost.

The optimal DA problem consists in finding the $m \times n$ binary association matrix $\mathbf{A} = [a(i,j)]$ with $a(i,j) \in \{0,1\}$, maximizing the global reward $R(\mathbf{\Omega}, \mathbf{A})$, given by:

$$R(\mathbf{\Omega}, \mathbf{A}) \triangleq \sum_{i=1}^{m} \sum_{j=1}^{n} \omega(i,j) a(i,j). \tag{1}$$

If $a(i,j) = 1$, it means that one has an association between target T_i and measurement $\mathbf{z}_j$. The association indicator value $a(i,j) = 0$ means that they are not associated.

$$a(i,j) = \begin{cases} 1, \text{ if } \mathbf{z}_j \text{ is associated to track } T_i \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

The importance of the assignment problem is quite clear and various successful solutions to its solving already exist. Among the well known are Kuhn-Munkres algorithm (known as Hungarian) [12], [13], and its extension proposed by Bourgeois and Lassalle in [14] to rectangular matrices. More sophisticated Murty's method [15] provides not only the first best assignment, but also the m-best assignments in order of increasing cost, as it was shown in the examples in [10], [11]. The best optimal assignment solution is not necessarily unique, as well as the second best one. Usually in MTT algorithms the first best assignment solution is taken as a hard decision for association. But in some real practical cases of dense multi-target and cluttered environment, DA problem is difficult to solve, because some of the associations decisions $a(i,j)$ are unreliable, so they could lead to potential mistakes.

For example, in case of incorrect determination of the incoming measurements for two tracks in such a way, that they are too close, the solution of the assignment problem, that is the core of the Global Nearest Neighbour (GNN) approach, is impossible to be sufficiently explicit. In such a case, it will be more cautious not to rely on all the pairings confirmed in the first best solution, no matter than only some of them are trustable enough. Utilizing the already obtained and available m-best assignments solutions, Dezert et al. [10], [11] provided an appealing method for taking into account this knowledge.

III. Quality Assessment of pairings in DA

In order to establish the quality of particular associations, associated with the optimal assignment matrix $\mathbf{A}_1$, and satisfying the condition $a_1(i,j) = 1$, QADA method proposes to utilize both, first and second assignment solutions $\mathbf{A}_1$ and $\mathbf{A}_2$. For a self-containing purpose, this section recalls briefly the principle of QADA that has been already detailed in [10], [11] with a tracking application in [17].

The main idea behind it is to compare the values $a_1(i,j)$ in $\mathbf{A}_1$ with the corresponding values $a_2(i,j)$ in $\mathbf{A}_2$, and to identify if there is a change of the optimal pairing (i,j). In our MTT context (i,j) means an association between measurement $\mathbf{z}_j$ and target T_i. One establishes a quality indicator associated with this pairing, depending on the stability of the pairing and also, on its relative impact in the global reward. The proposed method works also when the 1^{st} and 2^{nd} optimal assignments $\mathbf{A}_1$ and $\mathbf{A}_2$ are not unique, i.e., there are multiplicities available. The construction of the quality indicator is based on BF theory and Proportional Conflict Redistribution Rule no.6 (PCR6), defined within DSmT [8]. It depends on the type of the pairing matching, as it is described below:

- If $a_1(i,j) = a_2(i,j) = 0$, one has a full agreement on the hypothesis 'non-association' of the given pairing $(T_i, \mathbf{z}_j)$ in $\mathbf{A}_1$ and $\mathbf{A}_2$. This 'non-association' has no impact on the global reward values $R_1(\mathbf{\Omega}, \mathbf{A}_1)$ and $R_2(\mathbf{\Omega}, \mathbf{A}_2)$, therefore it will be useless to utilize it in DA. Hence, in this case, the quality indicator will be set to zero, $q(i,j) = 0$.
- If $a_1(i,j) = a_2(i,j) = 1$, one has a full agreement on the hypothesis 'association' of the pairing $(T_i, \mathbf{z}_j)$ in $\mathbf{A}_1$ and $\mathbf{A}_2$. This 'association' $(T_i, \mathbf{z}_j)$ has different impacts on the global reward values $R_1(\mathbf{\Omega}, \mathbf{A}_1)$ and $R_2(\mathbf{\Omega}, \mathbf{A}_2)$. In order to estimate the quality of this matching pairing, one establishes two Basic Belief Assignments (BBAs), $m_s(.), s = 1, 2$, according to both sources of information (1^{st} and 2^{nd} optimal assignments matrices $\mathbf{A}_1$ and $\mathbf{A}_2$). The frame of discernment consists of a single hypothesis $X = (T_i, \mathbf{z}_j)$: measurement $\mathbf{z}_j$ belongs to the track T_i. The ignorance is modelled by the proposition $X \cup \bar{X}$, where $\bar{X}$ is the negation of hypothesis X:

$$\begin{cases} m_s(X) = a_1(i,j).\omega(i,j)/R_1(\Omega, \mathbf{A}_1) \\ m_s(X \cup \bar{X}) = 1 - m_s(X) \end{cases} \tag{3}$$

  Applying the conjunctive rule of combination [8] (Vol. 1), one gets:

$$\begin{cases} m_{12}(X) = m_1(X)m_2(X) + m_1(X)m_2(X \cup \bar{X}) \\ \qquad\qquad + m_1(X \cup \bar{X})m_2(X) \\ m_{12}(X \cup \bar{X}) = m_1(X \cup \bar{X})m_2(X \cup \bar{X}) \end{cases} \tag{4}$$

  The pignistic transformation [16] is applied in order to obtain pignistic probabilities, built on the base of combined belief assignments, such as: $BetP(X) = m_{12}(X) + \frac{1}{2}.m_{12}(X \cup \bar{X})$ and $BetP(\bar{X}) = \frac{1}{2}.m_{12}(X \cup \bar{X})$. Then one chooses the quality indicator, associated with the pairing (i,j), as $q(i,j) = BetP(X)$.
- If $a_1(i,j) = 1$ and $a_2(i,j) = 0$, then a conflict is encountered on the association $(T_i, \mathbf{z}_j)$ in $\mathbf{A}_1$ and $\mathbf{A}_2$.

Then one could find the association (T_i, z_{j_2}) in $\mathbf{A}_2$, where j_2 is the index, such that $a_2(i, j_2) = 1$. In order to define the quality of such conflicting association, one establishes two BBAs, $m_s(.), s = 1, 2$ according to both sources of information ($\mathbf{A}_1$ and $\mathbf{A}_2$). The frame of discernment consists of two propositions: $\Theta = \{X = (T_i, \mathbf{z}_j), Y = (T_i, z_{j_2})\}$, and the BBAs are defined by [10].

$$\begin{cases} m_1(X) = a_1(i,j) \cdot \frac{\omega(i,j)}{R_1(\Omega,\mathbf{A}_1)} \\ m_1(X \cup Y) = 1 - m_1(X) \end{cases} \tag{5}$$

$$\begin{cases} m_2(Y) = a_2(i,j_2) \cdot \frac{\omega(i,j_2)}{R_2(\Omega,\mathbf{A}_2)} \\ m_2(X \cup Y) = 1 - m_2(Y) \end{cases} \tag{6}$$

Applying PCR6 fusion rule [8] (Vol. 3), one gets:

$$\begin{cases} m(X) = m_1(X).m_2(X \cup Y) + m_1(X) \cdot \frac{m_1(X)m_2(Y)}{m_1(X)+m_2(Y)} \\ m(Y) = m_1(X \cup Y).m_2(Y) + m_2(Y) \cdot \frac{m_1(X)m_2(Y)}{m_1(X)+m_2(Y)} \\ m(X \cup Y) = m_1(X \cup Y)m_2(X \cup Y) \end{cases} \tag{7}$$

Applying again the pignistic transformation, one gets $BetP(X) = m(X) + \frac{1}{2}.m(X \cup Y)$ and $BetP(Y) = m(Y) + \frac{1}{2}.m(X \cup Y)$. Hence, the quality indicators here are chosen as: $q(i,j) = BetP(X)$ and $q(i,j_2) = BetP(Y)$. The absolute quality factor becomes: $Q_{abs}(\mathbf{A}_,\mathbf{A}_2) = \sum_{i=1}^{m}\sum_{j=1}^{n} .a(i,j).q(i,j)$.
Once obtained, this quality matrix $\mathbf{Q} = [q(i,j)]$, $i = 1,\dots,m$; $j = 1,\dots,n$, where the elements $q(i,j) \in [0,1]$ define the quality of particular associations, chosen in the optimal assignment matrix $\mathbf{A}_1$. It will be utilized in the next step of the classical MTT algorithm - Kalman filtering (KF).

IV. Kalman filtering influenced by QADA method

The classical target tracking algorithm was run, consisting of two basic steps: (i) data association to associate the proper measurements (distance, angle) with correct targets and (ii) track filtering to update the targets state vectors, once the optimal assignment is found. In our simulation the Global Nearest Neighbour (GNN) [1] approach is applied in order to make a decision for data associations. GNN approach is a DA method that provides an assignment matrix for quality assessment of data association.

The Converted Measurement Kalman Filter (CMKF) is used for track filtering. We will not recall it in details, which can be found in many standard textbooks ([1], [2]), but will make an impact on the manner, in which the obtained quality assessment of pairings in the optimal assignment solution influences the target's state updating.

In order to derive KF equations, the goal is to find an equation computing an a posteriori state estimate $\hat{\mathbf{x}}(k{+}1|k{+}1)$ at time $(k+1)$ as a linear combination of an a priori estimate $\hat{\mathbf{x}}(k+1|k)$, and a weighted difference between the true measurement $\mathbf{z}(k+1)$ and a measurement prediction:

$$\hat{\mathbf{x}}(k+1|k+1) = \hat{\mathbf{x}}(k+1|k) + \mathbf{W}(k+1)\tilde{\mathbf{z}}(k+1) \tag{8}$$

The difference $\tilde{\mathbf{z}}(k+1) \triangleq \mathbf{z}(k+1) - \mathbf{H}\hat{\mathbf{x}}(k+1|k)$, called a measurement innovation (or residual), reflects the discrepancy between the predicted measurement $\hat{\mathbf{z}}(k+1|k) = \mathbf{H}(k+1)\hat{\mathbf{x}}(k+1|k)$ and the true one $\mathbf{z}(k+1)$, where $\mathbf{H}(k+1)$ is the so-called observation matrix. If $\tilde{\mathbf{z}}(k+1)$ is equal to zero, it means, that both, the true measurement and predicted one are in full agreement, which is the perfect case. The matrix $\mathbf{W}(k+1)$ is the filter's gain matrix obtained by minimizing the a posteriori estimate error covariance. It is given by the following formulae, where $\mathbf{R}$ is the measurement error covariance, and $\mathbf{P}(k+1|k)$ is the predicted covariance matrix of the state estimate error:

$$\mathbf{W}(k+1) = \mathbf{P}(k+1|k)\mathbf{H}^T(k+1)\mathbf{S}^{-1}(k+1) \tag{9}$$

$$= \mathbf{P}(k+1|k)\mathbf{H}^T(k+1) \cdot \left[\mathbf{H}(k+1)\mathbf{P}(k+1|k)\mathbf{H}^T(k+1) + \mathbf{R}\right]^{-1} \tag{10}$$

From Eqs. (8) and (10) one could conclude, that the value of measurement error covariance $\mathbf{R}$ influences the gain's value $\mathbf{W}(k{+}1)$, and respectively the state estimate in the way below:

- If the measurement error covariance $\mathbf{R} \rightarrow \mathbf{0}$, the true measurement $\mathbf{z}(k+1)$ is trusted more, and in the same time predicted measurement $\mathbf{H}\hat{\mathbf{x}}(k+1|k)$ is trusted less.
- If the measurement error covariance $\mathbf{R}$ increases, the true measurement $\mathbf{z}(k{+}1)$ is trusted less, and in the same time predicted measurement $\mathbf{H}\hat{\mathbf{x}}(k+1|k)$ is trusted more.

Let's now recall again what kind of information one obtains, having in hand the quality matrix, derived by QADA method [10]. It gives us a knowledge about the confidence $q(i,j)$ in all pairings $(T_i, \mathbf{z}_j), i = 1,..,m; j = 1,..,n$, chosen in the first best assignment solution. The smaller quality (confidence) of hypothesis "$\mathbf{z}_j$ *belongs to* T_i" means, that the particular measurement error covariance $\mathbf{R}$ was increased and one should not trust fully in the actual (true) measurement $\mathbf{z}(k+1)$.

Having this conclusion in mind, in this work we propose, such a behaviour of the measurement error covariance to be modelled by $\mathbf{R} = \frac{\mathbf{R}}{q(T_i,\mathbf{z}_j)}$, for every pairing, chosen in the first best assignment and on the base of corresponding quality value obtained. Then, Kalman filter gain decreases, and as a result, the true measurement $\mathbf{z}_j(k+1)$ is trusted less in the updated state estimate $\hat{\mathbf{x}}(k+1|k+1)$.

The MTT algorithm tested in this paper is based on the classical one (using Kalman Filters based on kinematics measurements) because we are only concerned with impact QADA on the performances of such type of tracking filters for now. Our aim is not to compare this QADA-MTT to other more sophisticate MTT algorithms[1], but we believe that QADA approach could also be useful for improving performances of more sophisticate MTT algorithms as well. This is left for future research works.

[1]In fact, we will just compare QADA-MTT to KDA-MTT and GDA-MTT based on CMKF in Section V.

V. Simulation scenarios and results

Two simulation MTT scenarios - non-maneuvering and maneuvering are presented and the results, obtained on the base of QADA-, KDA-, and GDA based MTT are discussed.

A. Maneuvering targets simulation scenario

The simulation scenario (Fig. 1) consists of three air targets with two classes. The stationary sensor is located at the origin. The sampling period is $T_{scan} = 5sec$ and the measurement standard deviations are 0.4 deg and 25m for azimuth and range respectively. The targets go from West to East with the following type order CFC (C=Cargo, F=Fighter) with constant velocity $100m/sec$. At the beginning the targets move from different directions. The first target moves from North-West with heading 120 degrees from North. At $scan\,no. = 8$ the target performs a maneuver until $scan\,no. = 15$ with transversal acceleration $+1.495m/s^2$ and settles towards East, moving in parallel according to X axis. The second target moves during the whole scenario in parallel according to X from West to East without maneuvering. The third target at the beginning moves from South-West with heading 60 degrees from North. At $scan\,no. = 8$ the target performs a maneuver until $scan\,no. = 15$ with transversal acceleration $-1.495m/s2$ and settles towards East, moving in parallel according to X axis. The inter-distance between the targets during scans 15th - 18th (the parallel segment) is approximately 150m. At $scan\,no. = 18$ to $scan\,no. = 25$ the first and the third targets make new maneuvers. The first one is directed to North-East and the second - to South-East. The process noise standard deviations for the two nested models for constant velocity IMM (Interacting Multiple Models) filter [1], [3] are $0.1m/s^2$ and $7m/s^2$ respectively. The number of false alarms (FA) follows a Poisson distribution and FA are uniformly distributed in the surveillance region.

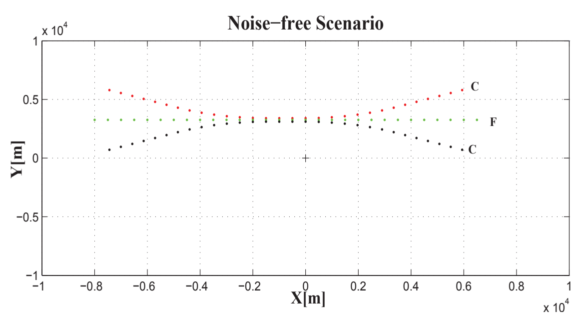

Figure 1. Noise-free maneuvering MTT Scenario.

Fig. 2 shows the respective noised scenario.

GDA-MTT [6], [7] improves DA process by utilizing target's type decision based on the confusion matrix $\mathbf{C} = [C_{ij}]$ coupled with the classical kinematic measurements, where $C_{ij} = P(T_d = T_j / TrueTargetType = T_i)$ represents the probability of decisions $T_d = (T_1 \triangleq Fighter, T_2 \triangleq Cargo)$, that the target type is j when its real type is i. In our simulation $\mathbf{C} = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$.

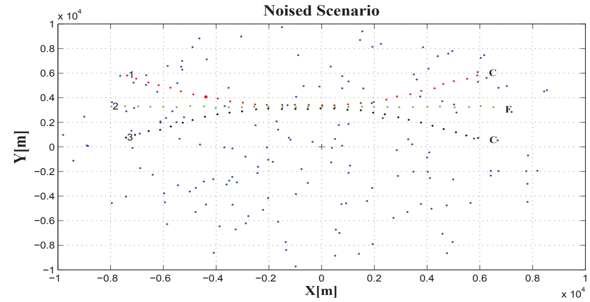

Figure 2. Noised maneuvering MTT Scenario.

Monte Carlo (MC) simulations for the considered MTT scenario are made for 200 MC runs, applying KDA, QADA, and GDA. Our goal is to evaluate, show, and to discuss the effect of Quality Assessment of Optimal Assignment for Data Association on the overall target tracking performance in comparison to results, obtained for the same scenario, by Kinematic only Data Association, and Generalized Data Association based MTT. We use an idealized track initiation in order to prevent uncontrolled impact of this stage on the statistical parameters of the tracking process during Monte Carlo tests of the new developed algorithm. The true targets positions (known in our simulations) for the first two scans are used for tracks initiation.

The evaluation of MTT performance is based on the criteria of tracks' purity, tracks' life, and percentage of miscorrelation. Track's purity criteria examines the ratio between the number of particular performed (jth observation - ith track) associations (in case of detected target) over the total number of all possible associations during the tracking scenario. Track's life is evaluated as an average number of scans before track's deletion. In our simulations, a track is cancelled and deleted from the list of tracked tracks, when during 3 consecutive scans it cannot be updated with some measurement because there is no validated measurement in the validation gate. We call this, the "cancelling/deletion condition". The status of the tracked tracks is denoted "alive".

The percentage of miscorrelation examines the relative number of incorrect (observation-to-track) associations during the scans.

The results for less noised case (with 0.2 FA in average in the filter validation gate) are given in Table 1.

Table I

Maneuvering scenario: Comparison between KDA, QADA, GDA based MTT performances for $FA = 0.2$.

	KDA-MTT	**QADA-MTT**	GDA-MTT
Average Track Life [%]	86.65	**92.82**	91.06
Average Miscorrelation [%]	7.27	**3.69**	3.06
Track Purity [%]	77.44	**88.20**	85.74

QADA-MTT exceeds KDA-MTT according to average track life and track purity, and shows better performance concerning the encountered average track life in comparison to GDA-MTT. Figure 3 shows the most informative knowledge - a percentage of miscorrelations, encountered during the consecutive scans. One could see, that QADA-MTT shows almost two times better performance in comparison to KDA-MTT, and is close to GDA-MTT performance.

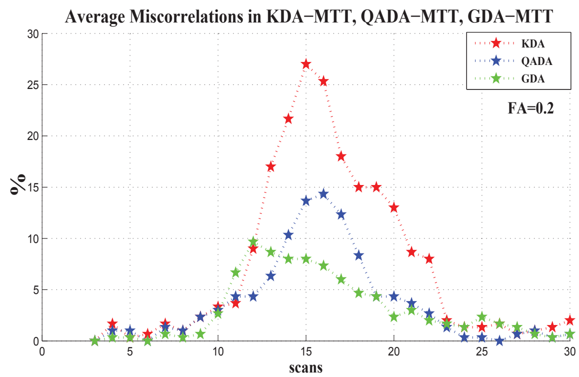

Figure 3. Maneuvering scenario: Average miscorrelations in KDA-MTT, QADA-MTT, GDA-MTT for noised case $FA = 0.2$

The respective results for the most noised case (with 0.4 FA in average in the filter validation gate) are given in Table 2 below.

Table II
MANEUVERING SCENARIO: COMPARISON BETWEEN KDA, QADA, GDA BASED MTT PERFORMANCES FOR $FA = 0.4$

	KDA-MTT	**QADA-MTT**	GDA-MTT
Average Track Life [%]	74.27	**86.61**	86.52
Average Miscorrelation [%]	10.58	**7.05**	4.68
Track Purity [%]	60.42	**77.96**	79.35

As a whole, the results for $FA = 0.4$ are deteriorated in comparison to the less noised case, but still QADA-MTT shows stably better performance with respect to KDA-MTT performance. The average track life keeps a little bit higher than in GDA-MTT case.

The Fig.4, showing the percentage of miscorrelations in more difficult noised case, confirms that QADA-MTT overcomes KDA-MTT performance.

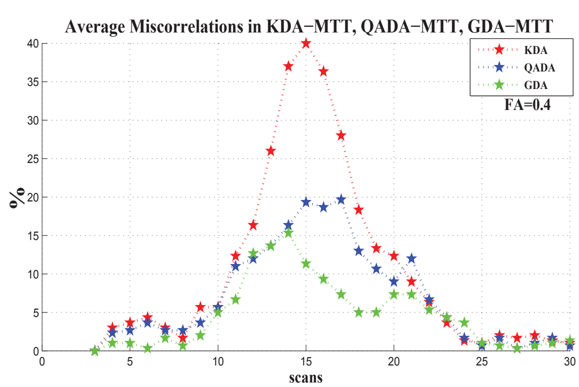

Figure 4. Maneuvering scenario: Average miscorrelations in KDA-MTT, QADA-MTT, GDA-MTT for noised case $FA = 0.4$

The figures 5 and 6 show typical performances of QADA-MTT and KDA-MTT systems.

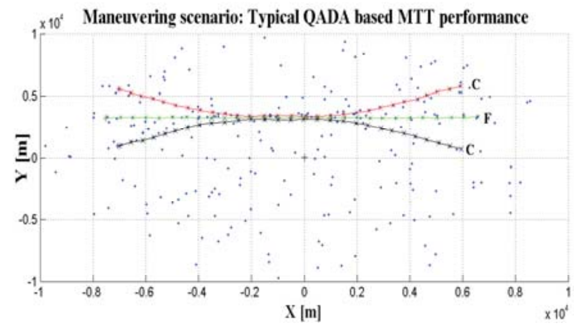

Figure 5. Maneuvering scenario: Typical performance of QADA based MTT.

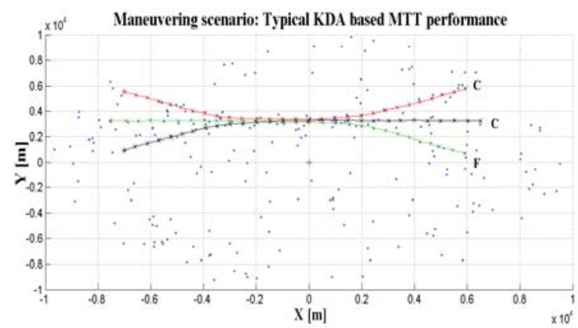

Figure 6. Maneuvering scenario: Typical performance of KDA based MTT.

The figures 7 and 8 show the averaged filtered errors along X (designated by asterisk) and Y (designated by circles) axes, and the distance error associated with the maneuvering track 1 in the considered scenario.

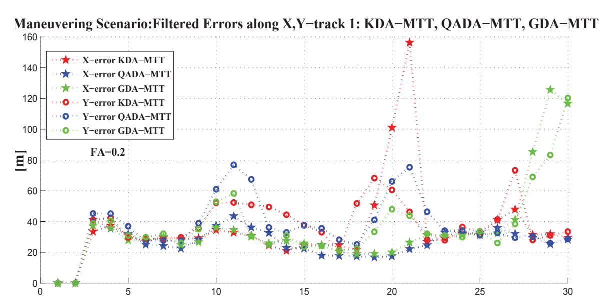

Figure 7. Filtered errors along X,Y for maneuvering track 1 - KDA-MTT, QADA-MTT, GDA-MTT.

For the maneuvering target 1, the errors, along X axis, obtained by using QADA-MTT, are definitely smaller than those, encountered with KDA-MTT. The errors along Y are a little bit bigger than respective errors along X, but as a whole the distance error, encountered by using QADA-MTT are smaller than in KDA-MTT. MC errors are evaluated on the base of the averaged errors associated with all “alive” tracks. Some of the errors occurred (for example in Fig.7 and Fig.8)

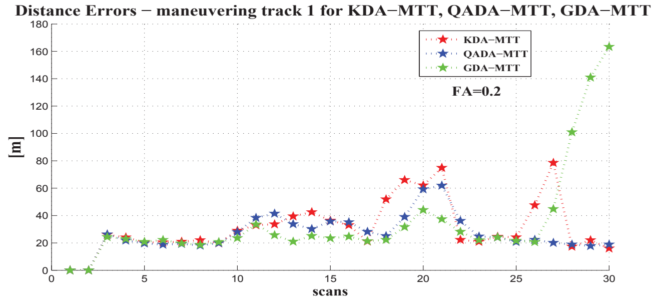

Figure 8. Maneuvering scenario: Distance errors for maneuvering track 1 - KDA-MTT, QADA-MTT, GDA-MTT.

could be explained by the unrealized canceling of tracks at the end of the scenario, when some tracks go toward canceling, but cannot satisfy the canceling condition because of lack of time. As a result they are not cancelled (and not deleted) leading that way to the increasing error.

Figures 9 and 10 show the behaviour of the same errors, but now associated with the near-by non-maneuvering target 2.

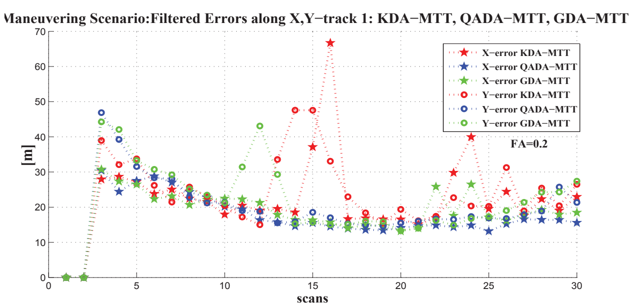

Figure 9. Maneuvering scenario: Filtered errors along X,Y for non-maneuvering track 2 - KDA-MTT, QADA-MTT, GDA-MTT.

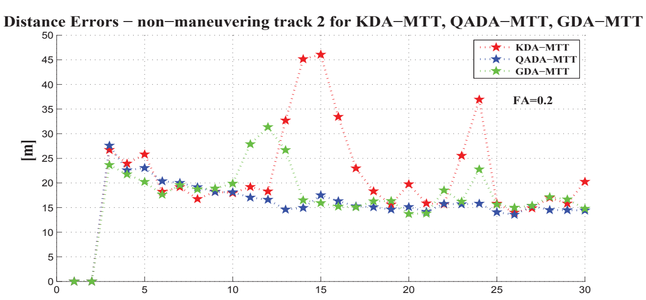

Figure 10. Maneuvering scenario: Distance errors for non-maneuvering track 2 - KDA-MTT, QADA-MTT, GDA-MTT.

For the non maneuvering target 2, the filtered errors along X and Y axes, obtained by using QADA-MTT, are smooth and definitely smaller then those, encountered with KDA-MTT. As a consequence, the associated with QADA-MTT distance error is smaller than in KDA- and GDA-MTT. The errors are calculated on the base only of the "alive" tracks.

B. *Non-maneuvering targets simulation scenario*

The noise-free non-maneuvering targets simulation scenario (see Fig.11) consists of three air targets moving in parallel from West to East with the type order CFC (C=Cargo, F=Fighter) with constant velocity of $100m/sec$ and a distance between them $150m$. The stationary sensor is located at the origin. The sampling period is $T_{scan} = 5sec$, and the measurement standard deviations are 0.5 deg and 65m for azimuth and range respectively. The surveillance of moving targets is performed during 15 scans. The confusion matrix, utilized by GDA is $C = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$. Fig. 12 shows the respective noised scenario.

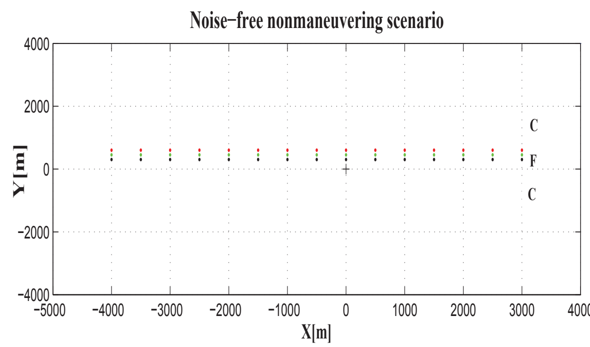

Figure 11. Noise-free non-maneuvering MTT Scenario.

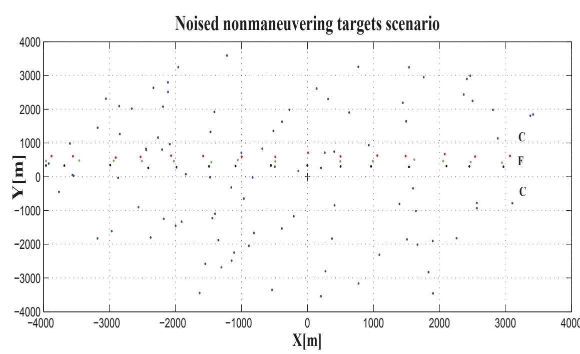

Figure 12. Noised non-maneuvering MTT Scenario.

As reported in Table 3, QADA-MTT shows again almost 2 times better performance, in comparison to KDA-MTT, according to the average miscorrelations, and also better performance regarding the average track life and track purity.

Table III
NON-MANEUVERING SCENARIO: COMPARISON BETWEEN KDA, QADA, GDA BASED MTT PERFORMANCES FOR $FA = 0.2$.

	KDA-MTT	**QADA-MTT**	GDA-MTT
Average Track Life [%]	89.79	**94.21**	97.59
Average Miscorrelation [%]	21.36	**10.77**	5.82
Track Purity [%]	64.46	**81.72**	90.15

Fig.13 shows the percentage of miscorrelations in less noised case (with 0.2 FA in average per gate).

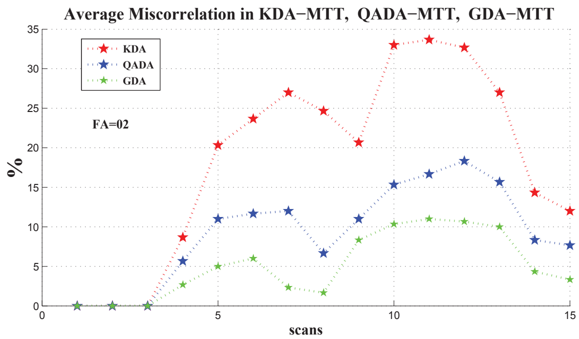

Figure 13. Non-maneuvering scenario: Average miscorrelations in KDA-MTT, QADA-MTT, GDA-MTT.

The same QADA-MTT behaviour is valid in the more dense cluttered environment with 0.4 FA in average per gate (see table 4 and fig. 14).

Table IV
NON-MANEUVERING SCENARIO: COMPARISON BETWEEN KDA, QADA, GDA BASED MTT PERFORMANCES FOR $FA = 0.4$.

	KDA-MTT	**QADA-MTT**	GDA-MTT
Average Track Life [%]	90.72	**92.18**	96.77
Average Miscorrelation [%]	20.69	**12.15**	6.26
Track Purity [%]	65.46	**77.38**	88.82

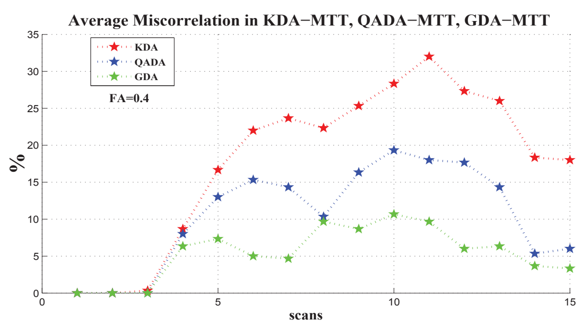

Figure 14. Non-maneuvering scenario: Average miscorrelations in KDA-MTT, QADA-MTT, GDA-MTT.

The figures 15 and 16 show typical performances of QADA-MTT and KDA-MTT systems.

The figures 17–20 show the encountered filtered errors along X and Y axes and the distance errors, associated with the intermediate track 2 for both noised cases (when the number of FA per gate is 0.2 and 0.4).

One observes (for example in Fig.9 and Fig.17) that errors associated with this simpler (non-maneuvering) scenario sometimes appear to be greater than in the previous more complicated (maneuvering) one. It is because the sensor's errors are defined deliberately greater in the non-maneuvering scenario. It provokes a complex situations, where the impact of QADA method is better demonstrated.

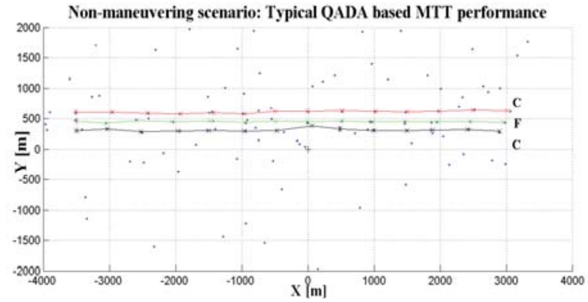

Figure 15. Non-maneuvering scenario: Typical performance of QADA based MTT.

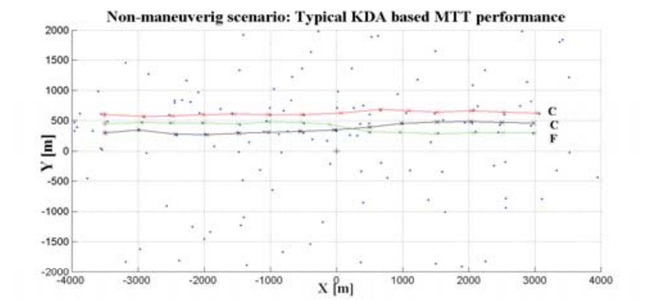

Figure 16. Non-maneuvering scenario: Typical performance of KDA based MTT.

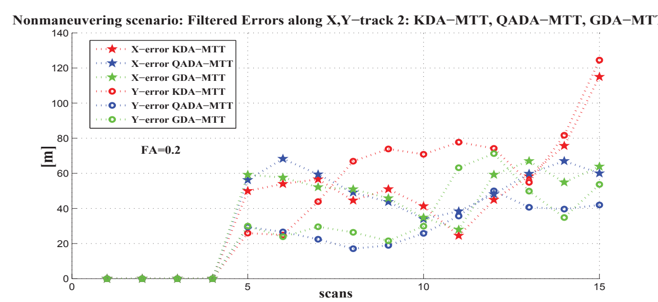

Figure 17. Non-maneuvering scenario: Filtered errors along X,Y for track 2 - KDA-MTT, QADA-MTT, GDA-MTT.

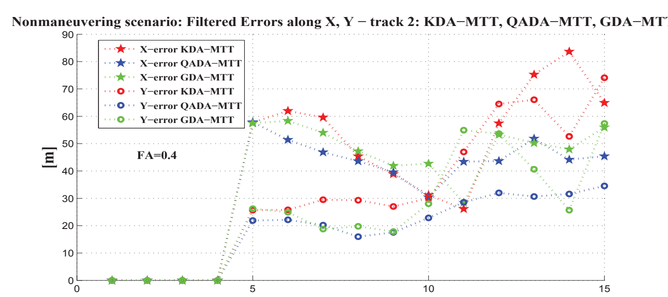

Figure 18. Non-maneuvering scenario: Filtered errors along X,Y for track 2 - KDA-MTT, QADA-MTT, GDA-MTT.

VI. CONCLUSIONS

This work assesses the efficiency of MTT performance in cluttered conflicting situations, based on the recent QADA

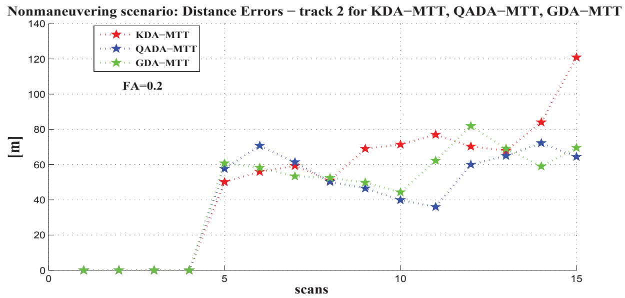

Figure 19. Non-maneuvering scenario: Distance errors for non-maneuvering track 2 - KDA-MTT, QADA-MTT, GDA-MTT.

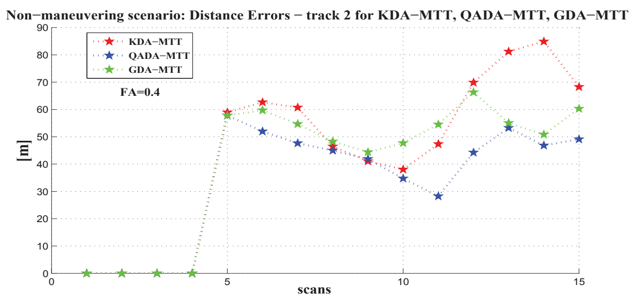

Figure 20. Non-maneuvering scenario: Distance errors for non-maneuvering track 2 - KDA-MTT, QADA-MTT, GDA-MTT.

method. The QADA based MTT performance is compared with the results, obtained for KDA and GDA based MTT, concerning two (maneuvering and non-maneuvering targets) scenarios. Our Monte Carlo simulation results show that QADA-MTT performs better than KDA-MTT for all measures of performances in all scenarios under low or heavy clutter conditions with target detection probabilities less than one, which is the main result of this paper.

Concerning the comparison of performances of QADA-MTT (using kinematics measurements only) with respect to GDA-MTT, we observe that the performances of GDA-MTT are slightly better than those of QADA-MTT. This conclusion is not very surprising because GDA-MTT uses more information (kinematics and attributes) than KDA-MTT or QADA-MTT (which are based on kinematics measurements only). Therefore, the ability of GDA-MTT to provide better tracking performances is what we naturally expect. However, we must emphasize that QADA method could also be used to improve GDA-MTT as well in a similar manner as it has been used to improve the performances of KDA-MTT. This possible improvement of GDA-MTT with QADA is under investigation and will be reported in a forthcoming publication.

Taking in mind, that MTT problems as a general do not able to utilize additional target attribute information, (i.e. when only kinematic measurements are available), applying QADA instead of KDA leads to better MTT performance, because of its ability to estimate the quality of the individual pairings given in the optimal assignment solution. QADA is totally independent of the applied logic to obtain the best DA solution. Hence, it could be applied successfully in all cases when attribute or/and kinematic data are available.

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