J. Dezert[1], A. Tchamova[2], T. Semerdjiev[3], P. Konstantinova[4]

[1]ONERA, 29 Av. de la Division Leclerc, 92320 Chatillon, France
[2,3,4]Institute for Parallel Processing, Bulgarian Academy of Sciences, "Acad. G. Bonchev" Str., bl.25-A, 1113 Sofia, Bulgaria

Multitarget Tracking in Clutter based on Generalized Data Association: Performance Evaluation of Fusion Rules

Published in:
Florentin Smarandache & Jean Dezert (Editors)
Advances and Applications of DSmT for Information Fusion
(Collected works), Vol. II
American Research Press, Rehoboth, 2006
ISBN: 1-59973-000-6
Chapter XII, pp. 305 - 321

Abstract: *The objective of this chapter is to present and compare different fusion rules which can be used for Generalized Data Association (GDA) for multitarget tracking (MTT) in clutter. Most of tracking methods including Target Identification (ID) or attribute information are based on classical tracking algorithms such PDAF, JPDAF, MHT, IMM, etc. and either on the Bayesian estimation and prediction of target ID, or on fusion of target class belief assignments through the Dempster-Shafer Theory (DST) and Dempster's rule of combination. The main purpose of this study is to pursue our previous works on the development of a new GDA-MTT based on Dezert-Smarandache Theory (DSmT) but compare it also with standard fusion rules (Dempster's, Dubois & Prade's, Yager's) and with the new fusion rules: Proportional Conflict Redistribution rule No.5(PCR5), fusion rule based on T-Conorm and T-Norm Fuzzy Operators(TCN rule) and the Symmetric Adaptive Combination (SAC) rule. The goal is to assess the efficiency of all these different fusion rules for the applied GDA-MTT in critical, highly conflicting situation. This evaluation is based on a Monte Carlo simulation for a particular difficult maneuvering MTT problem in clutter.*

This work is partially supported by MONT grants I1205/02, MI-1506/05 and by Center of Excellence BIS21++ grant (FP6-2004-ACC-SSA-2).

12.1 Introduction

The idea of incorporating Target Identification (ID) information or target attribute measurements into classical (i.e. kinematics-based) tracking filters to improve multitarget tracking systems is not new and many approaches have been proposed in the literature over the last fifteen years. For example, in [14, 15, 21] an improved PDAF (Probabilistic Data Association Filter) had been developed for autonomous navigation systems based on Target Class ID and ID Confusion matrix, and also on another version based on imprecise attribute measurements combined within Dempster's rule. At the same time Lerro in [20] developed the AI-PDAF (Amplitude Information PDAF). Since the nineties many improved versions of classical tracking algorithms like IMM, JPDAF, IMM-PDAF, MHT, etc. including attribute information have been proposed (see [12] and [6] for a recent overview). Recent contributions have been done by Blasch and al. in [7–10, 31] for Group Target Tracking and classification. In last two years efforts have been done also by Hwang and al. in [17–19]. We recently discovered that the Hwang's MTIM (Multiple-target Tracking and Identity Management) algorithm is very close to our Generalized Data Association GDA-MTT. The difference between MTIM and GDA-MTT lies fundamentally in the Attribute Data Association procedure. MTIM is based on MAJPDA (Modified Approximated JPDA) coupled with RMIMM (Residual-mean Interacting Multiple Model) algorithm while the GDA-MTT is based on GNN (Global Nearest Neighbour) approach for data association incorporating both kinematics and attribute measurements (with more sophisticated fusion rules dealing with fuzzy, imprecise and potentially highly conflicting target attribute measurements), coupled with standard IMM-CMKF(Converted Measurement Kalman Filter) [1, 5, 23]. The last recent attempt for solving the GDA-MTT problem was proposed by Bar-Shalom and al. in [6] and expressed as a multiframe assignment problem where the multiframe association likelihood was developed to include the target classification results based on the confusion matrix that specifies the prior accuracy of the target classifier. Such multiframe s-D assignment algorithm should theoretically provide performances close to the optimality for MTT systems but remains computationally greedy. The purpose of this chapter is to compare the performances of several fusion rules usable into our new GDA-MTT algorithm based on a difficult MTT scenario with eleven closely spaced and maneuvering in some regions targets, belonging only to two classes within clutter and with only 2D kinematical measurements and attribute measurement.

This chapter is organized as follows. In section 12.2 we present our approach for GDA-MTT algorithm emphasizing only on the new developments in comparison with our previous GDA-MTT algorithm, developed in [26, 29]. In our previous works, we proved the efficiency of GDA-MTT (in term of Track Purity Performance) based on the DSm Hybrid rule of combination over the GDA-MTT based on Dempster's rule but also over the KDA-MTT (Kinematics-only-based Data Association) trackers on simple two targets scenarios (with and without clutter). In section 12.3 we remind the main fusion rules we investigate for our new GDA-MTT algorithm. Most of these rules are well-known in the literature [24, 26], but the PCR5, TCN and SAC rules presented here, which are really new ones, were recently proposed in [16, 27, 28, 30]. Due to space limitations, we assume that the reader is familiar with basics on Target Tracking [2–5, 11, 12], on DST [25] and on DSmT [26] for fusion of uncertain, imprecise and possibly highly conflicting information. Section 12.4 presents and compares several Monte Carlo results for different versions of our GDA-MTT algorithm based on the fusion rules proposed in section 12.3 for a particular MTT scenario. Conclusion is given in section 12.5.

12.2 General principle of GDA-MTT

Classical target tracking algorithms consist mainly in two basic steps: *data association* to associate proper measurements (usually kinematics measurement $\mathbf{z}(k)$ representing either position, distance, angle, velocity, acceleration, etc.) with correct targets and *track filtering* to estimate 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 (or at least as best as possible) observations to existing tracks (or eventually new born targets). The data association problem is very difficult to solve in dense multi-target and cluttered environment. To eliminate unlikely (kinematics-based) observation-to-track pairings, the classical validation test is carried on the Mahalanobis distance $d^2(i,j) \triangleq (\mathbf{z}_j(k) - \hat{\mathbf{z}}_i(k|k-1))'\mathbf{S}^{-1}(k)(\mathbf{z}_j(k) - \hat{\mathbf{z}}_i(k|k-1)) \leq \gamma$ 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). 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 coupled with a classical IMM (Interacting Multiple Model) for maneuvering target tracking is used to update the targets' state vectors.

This new GDA-MTT improves data association process by adding attribute measurements (like amplitude information or RCS (radar cross section)), or eventually as in [6] Target ID decision coupled with confusion matrix, to classical kinematical measurements to increase the performance of the MTT system. When attribute data are available, the generalized (kinematics and attribute) likelihood ratios are used to improve the assignment. The GNN approach is used in order to make a decision for data association. Our new GDA approach consists in choosing a set of assignments $\{\chi_{ij}\}$, for $i = 1, \dots n$ and $j = 1, \dots, m$, that assures maximum of the total generalized likelihood ratio sum by solving the classical assignment problem $\min \sum_{i=1}^{n} \sum_{j=1}^{m} a_{ij}\chi_{ij}$ using the extended Munkres algorithm [13] and 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 kinematics and attribute likelihood ratios respectively, and

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

and where the elements a_{ij} of the assignment matrix $\mathbf{A} = [a_{ij}]$ take the following values [22]:

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

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 [13]. As a result one obtains the optimal measurements to tracks association. Once the optimal assignment is found, i.e. the (what we feel) correct association is available, then standard tracking filter is used depending on the dynamics of the target under tracking. We will not recall classical tracking filtering methods here which can be found in many standard textbooks [5, 12].

12.2.1 Kinematics Likelihood Ratios for GDA

The kinematics likelihood ratios $LR_{\text{k}}(i,j)$ involved into a_{ij} are quite easy to obtain because they are based on classical statistical models for spatial distribution of false alarms and for correct measurements [5]. $LR_{\text{k}}(i,j)$ is evaluated as $LR_{\text{k}}(i,j) = LF_{\text{true}}(i,j)/LF_{\text{false}}$ where LF_{true} is the likelihood function that the measurement j originated from target (track) i and LF_{false} the likelihood function that the measurement j originated from false alarm. At any given time k, LF_{true} is defined[1] as $LF_{\text{true}} = \sum_{l=1}^{r} \mu_l(k) LF_l(k)$ where r is the number of the models (in our case of two nested models $r = 2$ is 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 is originated from target (track) i according to the model l, i.e. $LF_l(k) = \frac{1}{2\pi\sqrt{|\mathbf{S}_l^i(k)|}} e^{-d_l^2(i,j)/2}$. LF_{false} is defined as $LF_{\text{false}} = P_{fa}/V_c$, 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.

12.2.2 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 $LR_{\text{a}}(i,j)$ 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 proposed in [29]. A particular confusion matrix is constructed to model the sensor's classification capability. This work presents different possible issues to evaluate $LR_{\text{a}}(i,j)$ depending on the nature of the attribute information and the fusion rules used to predict and to update each of them. The specific attribute likelihood ratios are derived within both DSmT and DST frameworks.

12.2.2.1 Modeling the Classifier

The way of constructing the confusion matrix is based on some underlying decision-making process based on specific attribute features measurements. In this particular case, it is based on the fuzzification interface, described in our previous work [26, 29]. Through Monte Carlo simulations, the confusion matrix for two different average values of RCS is obtained, in terms of the first frame of hypotheses $\Theta_1 = \{(\text{S})\text{mall}, (\text{B})\text{ig}\}$. Based on the fuzzy rules, described in [29], defining the correspondence between RCS values and the respective targets' types, the final confusion matrix $\mathbf{T} = [t_{ij}]$ in terms of the second frame of hypotheses $\Theta_2 = \{(\text{F})\text{ighter}, (\text{C})\text{argo}\}$ is constructed. Their elements t_{ij} represent the probability to declare that the target type is i when its real type is j. Thus the target's type probability mass vector for classifier output is the j-th column of the confusion matrix $\mathbf{T}$. When false alarms arise, their mass vector consists in an equal distribution of masses among the two classes of targets.

12.2.2.2 Attribute Likelihood Ratio within DSmT

The approach for deriving $LR_{\text{a}}(i,j)$ within DSmT is based on relative variations of pignistic probabilities [26] for the target type hypotheses, H_j ($j = 1$ for Fighter, $j = 2$ for Cargo)

[1] where indexes i and j have been omitted here for LF notation convenience.

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 [26] that this approach outperforms most of the well-known ones for attribute data association. It is defined as:

$$\delta_i(P^*) = \frac{\mid \Delta_i(P^*|Z) - \Delta_i(P^*|\hat{Z} = T_i) \mid}{\Delta_i(P^*|\hat{Z} = T_i)} \tag{12.1}$$

where

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

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

12.2.2.3 Attribute Likelihood Ratio within DST

$LR_{\text{a}}(i,j)$ within DST is defined from the derived attribute likelihood function proposed in [3, 12]. If one considers the observation-to-track fusion process using Dempster's rule, the degree of conflict k_{ij} is computed as the assignment of mass committed to the conflict, i.e. $m(\emptyset)$. The larger this assignment is, the less likely is the correctness of observation j to track i assignment. Then, the reasonable choice for the attribute likelihood function is $LHF_{i,j} = 1 - k_{ij}$. The attribute likelihood function for the possibility that a given observation j originated from the false alarm is computed as $LHF_{fa,j} = 1 - k_{fa,j}$. Finally the attribute likelihood ratio to be used in GDA is obtained as $LR_{\text{a}}(i,j) = LHF_{i,j}/LHF_{fa,j}$.

12.3 Fusion rules proposed for GDA-MTT

Imprecise, uncertain and even contradicting information or data are characteristics of the real world situations and must be incorporated into modern MTT systems to provide a complete and accurate model of the monitored problem. On the other hand, the conflict and paradoxes' management in collected knowledge is a major problem especially during the fusion of many information sources. Indeed the conflict increases with the number of sources or with the number of processed scans in MTT. Hence a reliable issue for processing and/or reassigning the conflicting probability masses is required. Such a situation involves also some decision-making procedures based on specific data bases to achieve proper knowledge extraction for a better understanding of the overall monitored problem. It is important and valuable to achieve hierarchical extraction of relevant information and to improve the decision accuracy such that highly accurate decisions can be made progressively. There are many valuable fusion rules in the literature to deal with imperfect information based on different mathematical models and

on different methods for transferring the conflicting mass onto admissible hypotheses of the frame of the problem. DST [24, 25] was the first theory for combining uncertain information expressed as basic belief assignments with Dempster's rule.
Recently, DSmT [26] was developed to overcome the limitations of DST (mainly due to the well-known inconsistency of Dempster's rule for highly conflicting fusion problem and the limitations of the Shafer's model itself) and for combining uncertain, imprecise and possibly highly conflicting sources of information for static or dynamic fusion applications. DSmT is actually a natural extension of DST. The major differences between these two theories is on the nature of the hypotheses of the frame Θ on which are defined the basic belief assignments (bba) $m(.)$, i.e. either on the power set 2^Θ for DST or on the hyper-power set (Dedekind's lattice., i.e. the lattice closed by $\cap$ and $\cup$ set operators) D^Θ for DSmT. Let's consider a frame $\Theta = \{\theta_1, \ldots, \theta_n\}$ of finite number of hypotheses assumed for simplicity to be exhaustive. Let's denote G^Θ the classical power set of Θ (if we assume Shafer's model with all exclusivity constraints between elements of Θ) or denote G^Θ the hyper-power set D^Θ (if we adopt DSmT and we know that some elements can't be refined because of their intrinsic fuzzy and continuous nature). A basic belief assignment $m(.)$ is then defined as $m : G^\Theta \to [0, 1]$ with $m(\emptyset) = 0$ and $\sum_{X \in G^\Theta} m(X) = 1$. The differences between DST and DSmT lie in the model of the frame Θ one wants to deal with but also in the rules of combination to apply. Recently in [30] the authors propose to connect the combination rules for information fusion with particular fuzzy operators, focusing on the T-norm based Conjunctive rule as an analog of the ordinary conjunctive rule of combination. It is especially because the conjunctive rule is appropriate for identification problems, restricting the set of hypotheses one is looking for. A new fusion rule, called Symmetric Adaptive Combination (SAC) rule, has been recently proposed in [16] which is an adaptive mixing between the disjunctive and conjunctive rule.

The main fusion rules we have investigated in this work, already presented in details in Chapter 1 of this volume and in [26], are: Dempster's rule, Yager's rule, Dubois & Prade's rule, Hybrid DSm fusion rule, and PCR5 fusion rule. Moreover the two following fusion rules have been also tested and analyzed in this work:

- **T-Conorm-Norm fusion rule**

  The TCN (T-Conorm-Norm) rule represents a new class of combination rules based on specified fuzzy T-Conorm/T-Norm operators. It does not belong to the general Weighted Operator Class. This rule takes its source from the T-norm and T-conorm operators in fuzzy logics, where the AND logic operator corresponds in information fusion to the conjunctive rule and the OR logic operator corresponds to the disjunctive rule. The general principle of the new TCN rule developed in [30] consists in the following steps :

  - **Step 1**: Defining the min T-norm conjunctive consensus: The min T-norm conjunctive consensus is based on the default min T-norm function. The way of association between the focal elements of the given two sources of information is defined as $X = X_i \cap X_j$, and the degree of association is as follows:

$$\tilde{m}(X) = \min \{m_1(X_i), m_2(X_j)\}$$

where $\tilde{m}(X)$ represents[2] the mass of belief associated to the given proposition X by using T-Norm based conjunctive rule. The TCN Combination rule in Dempster Shafer Theory framework is defined for $\forall X \in 2^\Theta$ by the equation:

$$\tilde{m}(X) = \sum_{\substack{X_i \cap X_j = X \\ X_i, X_j \in 2^\Theta}} \min\{m_1(X_i), m_2(X_j)\} \tag{12.2}$$

– **Step 2**: Distribution of the mass, assigned to the conflict

The distribution of the mass, assigned to the obtained partial conflicts follows in some degree the distribution of conflicting mass in DSmT Proportional Conflict Redistribution Rule 5 [27], but the procedure here is based on fuzzy operators. Let us denote the two bbas, associated with the information sources in a matrix form:

$$\begin{bmatrix} m_1(.) \\ m_2(.) \end{bmatrix} = \begin{bmatrix} m_1(\theta_1) & m_1(\theta_2) & m_1(\theta_1 \cup \theta_2) \\ m_2(\theta_1) & m_2(\theta_2) & m_2(\theta_1 \cup \theta_2) \end{bmatrix}$$

The general procedure for fuzzy based PCR5 conflict redistribution is as follows:

* Calculate all partial conflicting masses separately;
* If $\theta_1 \cap \theta_2 = \emptyset$, then θ_1 and θ_2 are involved in the conflict; redistribute the corresponding masses $m_{12}(\theta_1 \cap \theta_2) > 0$ involved in the particular partial conflicts to the non-empty sets θ_1 and θ_2 with respect to the maximum between $m_1(\theta_1)$ and $m_2(\theta_2)$ and with respect to the maximum between $m_1(\theta_2)$ and $m_2(\theta_1)$;
* Finally, for the given above two sources the min T-Norm conjunctive consensus yields:

$$\tilde{m}(\theta_1) = \min(m_1(\theta_1), m_2(\theta_1)) + \min(m_1(\theta_1), m_2(\theta_1 \cup \theta_2)) + \min(m_1(\theta_1 \cup \theta_2), m_2(\theta_1))$$

$$\tilde{m}(\theta_2) = \min(m_1(\theta_2), m_2(\theta_2)) + \min(m_1(\theta_2), m_2(\theta_1 \cup \theta_2)) + \min(m_1(\theta_1 \cup \theta_2), m_2(\theta_2))$$

$$\tilde{m}(\theta_1 \cup \theta_2) = \min(m_1(\theta_1 \cup \theta_2), m_2(\theta_1 \cup \theta_2))$$

* The basic belief assignment, obtained as a result of the applied TCN rule with fuzzy based Proportional Conflict Redistribution Rule 5 becomes:

$$\tilde{m}_{PCR5}(\theta_1) = \tilde{m}(\theta_1) + m_1(\theta_1) \times \frac{\min(m_1(\theta_1), m_2(\theta_2))}{\max(m_1(\theta_1), m_2(\theta_2))} + m_2(\theta_1) \times \frac{\min(m_1(\theta_2), m_2(\theta_1))}{\max(m_1(\theta_2), m_2(\theta_1))}$$

$$\tilde{m}_{PCR5}(\theta_2) = \tilde{m}(\theta_2) + m_2(\theta_2) \times \frac{\min(m_1(\theta_1), m_2(\theta_2))}{\max(m_1(\theta_1), m_2(\theta_2))} + m_1(\theta_2) \times \frac{\min(m_1(\theta_2), m_2(\theta_1))}{\max(m_1(\theta_2), m_2(\theta_1))}$$

[2]We introduce in this chapter the over-tilded notation for masses to specify that the masses of belief are obtained with fuzzy T-norm operator.

– **Step 3**: Normalization of the result:
The final step of the TCN rule concerns the normalization procedure:

$$\tilde{m}_{PCR5}(X) = \frac{\tilde{m}_{PCR5}(X)}{\sum_{\substack{X \neq \emptyset \\ X \in 2^{\Theta}}} \tilde{m}_{PCR5}(X)} .$$

The nice features of the new rule could be defined as: very easy to implement, satisfying the impact of neutrality of Vacuous Belief Assignment; commutative, convergent to idempotence, reflecting majority opinion, assuring an adequate data processing in case of total conflict.

- **Symmetric Adaptive Combination rule**

The generic adaptive combination rule (ACR) is a mixing between the disjunctive and conjunctive rule and it is defined by $m_{ACR}(A) = 0$ and $\forall A \in 2^{\Theta}$ by:

$$m_{ACR}(A) = \alpha(k_{12}).m_{\cup}(A) + \beta(k_{12}).m_{\cap}(A) ,$$

where α and β are functions of the conflict $k_{12} = m_{\cap}(\emptyset)$ from $[0, 1]$ to $[0, +\infty]$. $m_{ACR}(.)$ must be a normalized bba(assuming a closed world) and a desirable behavior of ACR is that it should act more like the disjunctive rule whenever $k_{12} \to 1$ (at least one source is unreliable), while it should act more like the conjunctive rule, when $k_{12} \to 0$ (both sources are reliable). The three following conditions have to be satisfied by the weighting functions α and β:

– **C1**: α is increasing with $\alpha(0) = 0$ and $\alpha(1) = 1$;
– **C2**: β is decreasing with $\beta(0) = 1$ and $\beta(1) = 0$;
– **C3**: $\alpha(k_{12}) = 1 - (1 - k_{12})\beta(k_{12})$.

A symmetric AC (SAC rule) with symmetric weightings for $m_{\cap}(.)$ and $m_{\cup}(.)$ is defined by $m_{SAC}(\emptyset) = 0$ and $\forall A \in 2^{\Theta}$ by:

$$m_{SAC}(A) = \alpha_0(k_{12}).m_{\cup}(A) + \beta_0(k_{12}).m_{\cap}(A) ,$$

where

$$\alpha_0(k_{12}) = \frac{k_{12}}{1 - k_{12} + k_{12}^2} ;$$

$$\beta_0(k_{12}) = \frac{1 - k_{12}}{1 - k_{12} + k_{12}^2} .$$

12.4 Simulation scenario and results

12.4.1 Simulation scenario

The simulation scenario (Fig.12.1) consists of eleven air targets with only two classes. The stationary sensor is located at the origin. The sampling period is $T_{scan} = 5$ sec and measurement standard deviations are 0.3 deg and 100 m for azimuth and range respectively. The targets go from West to East in three groups with the following type order CFCFCFCFCFC (F=Fighter, C=Cargo) with constant velocity $100m/sec$. The first group consists of three targets (CFC) moving from North-West with heading 120 degrees from North. At scan number 15th the group performs a maneuver with transversal acceleration $5.2m/s^2$ and settles towards East, moving in parallel according to X axis. The second group consists of five closely spaced targets (FCFCF) moving in parallel from West to East without maneuvering. The third group consists of three targets (CFC) moving from South-West with heading 60 degrees from North. At scan number 15th the group performs a maneuver with transversal acceleration $-5.2m/s^2$ and settles towards East, moving in parallel according to X axis. The inter-distance between the targets during scans 17th - 48th (the parallel segment) is approximately 300 m. At scan number 48th the first and the third group make new maneuvers. The first one is directed to North-East and the second - to South-East. Process noise standard deviations for the two nested models for constant velocity IMM 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.

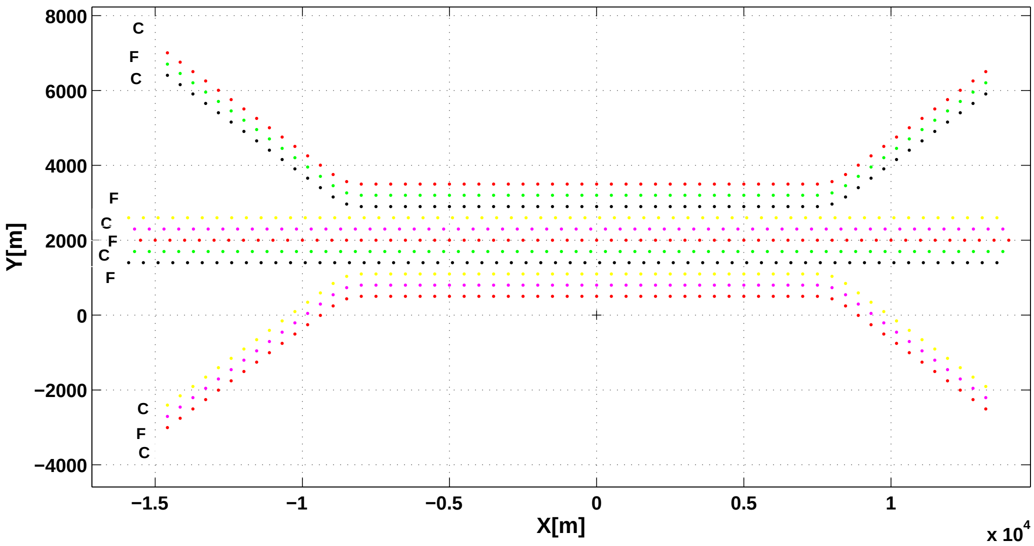

Figure 12.1: Multitarget Scenario with eleven targets

Monte Carlo simulations are made for two different average values of Radar Cross Section in order to obtain the confusion matrix in terms of the first frame of hypotheses $\Theta_1 = \{Small, Big\}$. According to the fuzzy rules in [26, 29], defining the correspondence between Radar Cross Section values and the respective targets' types, the confusion matrix in terms of the second frame of hypotheses $\Theta_2 = \{Fighter, Cargo\}$ is constructed. The two simulation cases correspond to the following parameters for the probability of target detection, the probability of false alarms and the confusion matrices:

- Case 1: $P_d = 1.0$, $P_{fa} = 0.0$, $T_1 = \begin{bmatrix} 0.995 & 0.005 \\ 0.005 & 0.995 \end{bmatrix}$

- Case 2: $P_d = 0.98$, $P_{fa} = 1.e^{-5}$, $T_2 = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$

12.4.2 Simulation results

In this section we present and discuss the simulation results for 100 Monte Carlo runs. The evaluation of fusion rules' performance is based on the criteria of tracks' purity, tracks' life, percentage of miscorrelation and variation of pignistic entropy in confirmed tracks' attribute states. Track's purity criteria examines the ratio between the number of particular performed (observation j-track i) 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. The track deletion is performed after the a priori defined number (in our case it is assumed to be 3) of incorrect associations or missed detections. The percentage of miscorrelation examines the relative number of incorrect (observation-track) associations during the scans. The results for GDA are obtained by different fusion rules. Relying on our previous work [26, 29], where the performance of DSm Classic and DSm Hybrid rules were examined, in the present work the attention is directed to the well-known Dempster's rule, Yager's, Dubois & Prade's, and especially to PCR5 and the new TCN and SAC rules. From results presented in Tables 12.1-12.4 in next sections, it is obvious that for both cases 1 and 2 the track's purity and tracks' life in the case of KDA-MTT are significantly lower with respect to all GDA-MTT, and a higher percentage of miscorrelation is obtained with KDA-MTT than with GDA-MTT. The figures 12.2 and 12.3 show typical tracking performances for KDA-MTT and GDA-MTT systems.

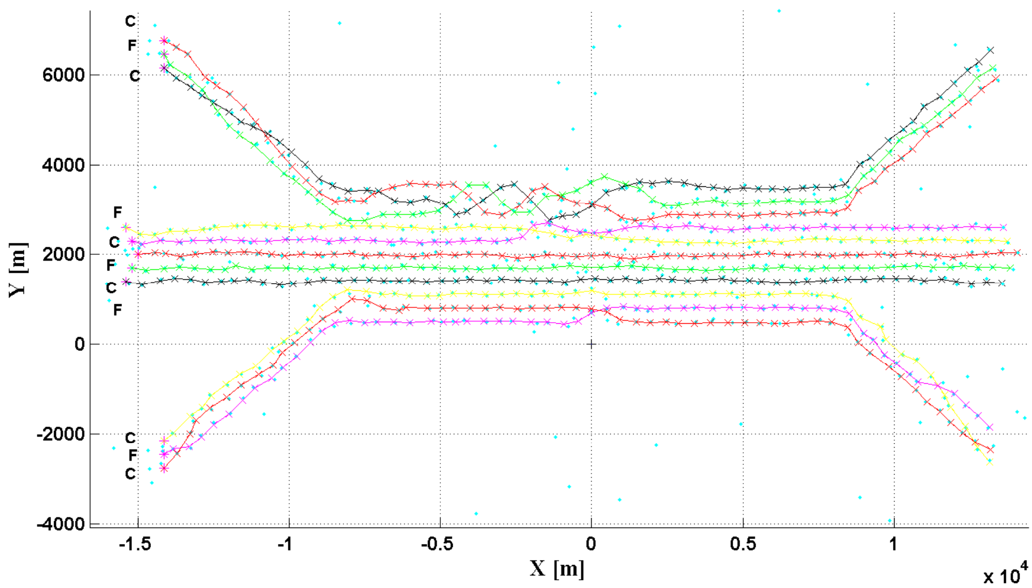

Figure 12.2: Typical performance with KDA-MTT

12.4.2.1 Simulation results for case 1

Case no. 1 is characterized by maximum probability of target detection, $P_d = 1$, probability of false alarms $P_{fa} = 0$, and well defined confusion matrix: $T_1 = \begin{bmatrix} 0.995 & 0.005 \\ 0.005 & 0.995 \end{bmatrix}$. The problem

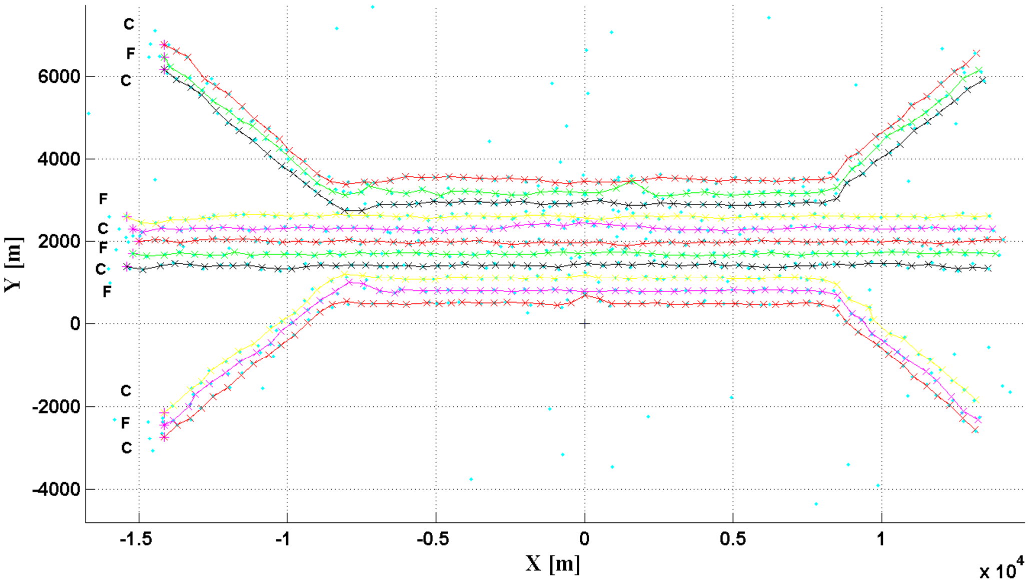

Figure 12.3: Typical performance with GDA-MTT

consists in the proximity of the targets (inter-distance of 300 m) with bad sensor distance resolution ($\sigma_D = 100m$). It results in cross-associations. The Monte Carlo results on track purity based on KDA-MTT and on GDA-MTT (based on PCR5, Dempster's (DS), Yager's (Y),Dubois & Prade's (DP) rule (DP) rules[3], DSmH) rule and the new TCN and SAC fusion rules) are given in Table 12.1. Each number of the table gives the ratio of correct measurement-target association for a given target and a given MTT algorithm and the last row of the table provides the average purity performance for all targets and for each algorithm.
One can see that the corresponding fields for results obtained via Dempster's rule of combination are empty (see Tables 12.1-12.4). There are two major reasons for this:

1. The case of increasing intrinsic conflicts between the fused bodies of evidence (generalized basic belief assignments of targets' tracks histories and new observations), yields a poor targets tracks' performance. The situation when this conflict becomes unity, is a stressful, but a real one. It is the moment, when Dempster's rule produces indefiniteness. The fusion process stops and the attribute histories of tracking tracks cannot be updated. As a result the whole tracking process corrupts. Actually in such a case there is a need of an artificial break and intervention into the real time tracking process, which could cause noncoherent results. Taking into account all these particularities, we can summarize that the fusion process within DST is not fluent and cannot be controlled without prior unjustified and artificial assumptions and some heuristic engineering tricks. As a consequence no one of the performance criteria cannot be evaluated.

2. In case when in the updated track's attribute history one of the hypotheses in the frame of

[3]Yager's rule, Dubois & Prade's (DP) rule, DSmH) rule coincide in our example because we are working with only a 2D specific classes frame Θ_2. This is normal. In general, Yager's, DP and DSmH) do no longer coincide when the cardinality of the frame becomes greater than two.

the problem is supported by unity, from this point on, Dempster's rule becomes indifferent to all observations, detected during the next scans. It means, the track's attribute history remains unchanged regardless of the new observations. It is a dangerous situation, which hides the real opportunity for producing the non-adequate results.

	KDA	PCR5	TCN	SAC	DS	DSmH/Y/DP/
T_1	0.4102	0.9971	0.9971	0.9971	-	0.9971
T_2	0.3707	0.9966	0.9769	0.9955	-	0.9953
T_3	0.4226	0.9990	0.9793	0.9979	-	0.9978
T_4	0.6198	0.9998	0.9703	0.9903	-	0.9903
T_5	0.5826	0.9997	0.9541	0.9902	-	0.9867
T_6	0.5836	1.0000	0.9743	1.0000	-	0.9964
T_7	0.6174	1.0000	0.9500	0.9900	-	1.0000
T_8	0.6774	0.9847	0.9478	0.9671	-	0.9847
T_9	0.4774	0.9426	0.9478	0.8812	-	0.9410
T_{10}	0.4241	0.9543	0.9645	0.7729	-	0.9528
T_{11}	0.4950	0.9595	0.9581	0.8238	-	0.9595
Average	0.5164	0.9848	0.9655	0.9460	-	0.9820

Table 12.1: Track's purity for KDA and GDA-MTT (case 1)

The results of the percentage of track's life duration and miscorrelation are given in Table 12.2.

Trackers	Track Life [%]	MisCor [%]
KDA-MTT	58.15	48.36
GDA$_{PCR5}$-MTT	98.75	1.52
GDA$_{TCN}$-MTT	97.03	3.45
GDA$_{SAC}$-MTT	95.23	5.40
GDA$_{DS}$-MTT	-	-
GDA$_{DSm/Y/DP}$-MTT	98.52	1.80

Table 12.2: Average Track's life and Miscorrelations (case 1)

The figure 12.4 shows the average variation of pignistic entropy in tracks' attribute histories during the scans, obtained by using different fusion rules (PCR5, TCN, SAC and DSmH/Y/DP). Looking on the results achieved according to GDA-MTT, it can be underlined that :

1. The tracks' purity, obtained by PCR5 and DSmH/Y/DP rules outperform the tracks' purity results obtained by using all other rules. In this 2D frame case based on Shafer's model DSmH/Y/DP tracks' purity results are equal which is normal. The TCN rule leads to a small (approximately 2 percent) decrease in GDA performance.

2. According to Table 12.2, the average tracks' life and the percentage of miscorrelation related to the performance of the PCR5 rule are a little bit better than the DSmH/Y/DP, and outperforms all other rules' results (approximately with 2 percent for TCN and with 3 percent for SAC rule).

3. According to the average values of pignistic entropy, associated with updated tracks' attribute histories during the consecutive scans (Fig.12.4), one can see that it is characterized with small values (for all fusion rules), in the interval $[0, 0.05]$. The entropy, obtained

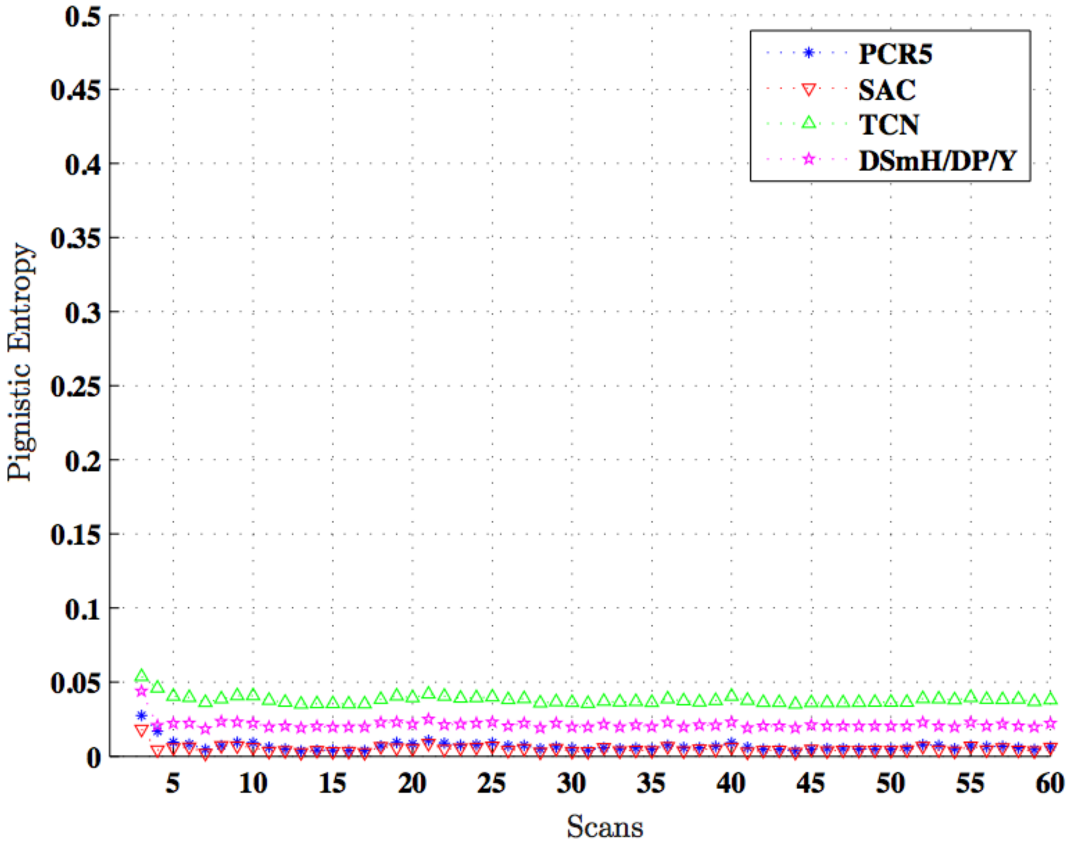

Figure 12.4: Average variation of Pignistic Entropy in tracks' attribute histories

via PCR5 and SAC rules demonstrates smallest values, approaching zero, following by DSmH/Y/DP and TCN fusion rules.

12.4.2.2 Simulation results for case 2

Case no. 2 ($P_d = 0.98$, $P_{fa} = 1.e^{-5}$, $T_2 = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$) is more difficult than case no.1 since the presence of false alarms and missed target detections significantly degrade the process of data association even in the case of GDA. But in comparison with KDA, one can see in Table 12.3 that the use of the attribute type information still helps to reduce the cross-associations and increases the track's purity performance. PCR5 rule behaves stable and keeps its best performance in this difficult case, followed by DSmH/Y/DP, SAC and TCN rules. While in case 1, the TCN performs very well (following PCR5 and DSmH/Y/DP), in case 2 it shows poor tracks' purity results, because of the fuzzy based processing and the confusion matrix's influence. The results of tracks' life duration and miscorrelation are given in Table 12.4.

The figure 12.5 shows the average variation of pignistic entropy in tracks' attribute histories during the scans, obtained by using different fusion rules (PCR5, TCN, SAC and DSmH/Y/DP) in case 2.

	KDA	PCR5	TCN	SAC	DS	DSmH/Y/DP/
T_1	0.3055	0.8138	0.3660	0.3971	-	0.6431
T_2	0.2717	0.7921	0.3219	0.3657	-	0.6252
T_3	0.3338	0.7907	0.3657	0.4024	-	0.6550
T_4	0.5114	0.8778	0.5074	0.6707	-	0.7709
T_5	0.4022	0.8164	0.4071	0.6074	-	0.7209
T_6	0.3712	0.8055	0.4588	0.6298	-	0.6922
T_7	0.4069	0.8098	0.4464	0.6043	-	0.6921
T_8	0.4545	0.8367	0.4974	0.6179	-	0.7359
T_9	0.7436	0.7436	0.4253	0.4886	-	0.6310
T_{10}	0.3040	0.7055	0.3931	0.4397	-	0.6202
T_{11}	0.3697	0.7621	0.4566	0.5086	-	0.6414
Average	0.3742	0.7958	0.4223	0.5211	-	0.6753

Table 12.3: Track's purity for KDA and GDA-MTT (case 2)

Trackers	Track Life [%]	MisCor [%]
KDA-MTT	45.87	62.58
GDA$_{PCR5}$-MTT	84.26	20.42
GDA$_{TCN}$-MTT	50.34	57.77
GDA$_{SAC}$-MTT	59.26	47.89
GDA$_{DS}$-MTT	-	-
GDA$_{DSm/Y/DP}$-MTT	73.29	32.47

Table 12.4: Average Track's life and Miscorrelations (case 2)

The variation of pignistic entropy in updated tracks' attribute histories, based on all fusion rules starts with peaks, because of the full ignorance, encountered in initial tracks' attribute states (initial tracks' histories). During the next 3-4 scans it decreases gradually and settles in the interval $[0.05 - 0.3]$. The pignistic entropies, obtained by PCR5 and SAC rules show smallest values. It means that in this more difficult case 2, PCR5 and SAC rules lead to results which are more informative in comparison with the other rules.

12.5 Conclusions

In this paper a comparison of the performances of different fusion rules is presented and compared in order to assess their efficiency for GDA for MTT in highly conflicting situations in clutter. A model of an attribute type classifier is considered on the base of particular input fuzzification interface according to the target RCS values and on fuzzy rule base according to the target type. A generalized likelihood ratio is obtained and included in the process of GDA. The classification results rely on the confusion matrix specifying the accuracy of the classifier and on the implemented fusion rules (Dempster's, Yager's, Dubois & Prade's, DSmH), PCR5, TCN and SAC). The goal was to examine their advantages and milestones and to improve association results. This work confirms the benefits of attribute utilization and shows some hidden drawbacks, when the sources of information remain in high conflict, especially in case of using Dempster's rule of combination. In clutter-free environment with maximum of target detection probability and very good classifier quality, the results, according to the performance criteria, obtained via PCR5 rule outperform the corresponding results obtained by using all

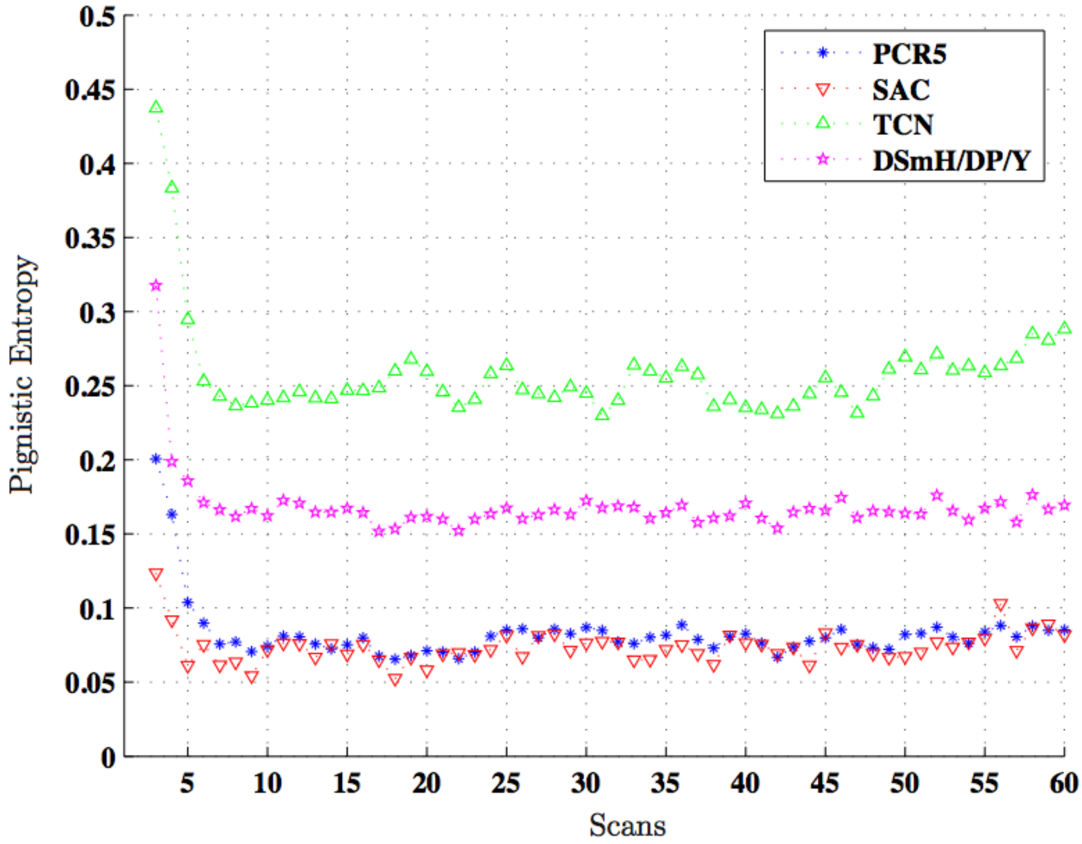

Figure 12.5: Average variation of Pignistic Entropy in tracks' attribute histories

the other combination rules tested. When tracking conditions decrease (presence of clutter, missed target detections with lower classifier quality), the PCR5 fusion rule still provides the best performances with respect to other rules tested for our new GDA-MTT algorithm. This work reveals also the real difficulty to define and to choose an unique or a multiple performance criteria for the fair evaluation of different fusion rules. Actually the choice of the fusion rule is in practice highly conditioned by the performance criteria that the system designer considers as the most important for his application. More efforts on multicriteria-based methods for performance evaluation are under investigations. Further works on GDA-MTT would be to define some precise benchmark for difficult multitarget tracking and classification scenarios and to see if the recent MITM approach (i.e. RMIMM coupled with MAJPDA) can be improved by our new generalized data association method.

12.6 References

[1] Angelova D., Jilkov V., Semerdjiev Tz., *Tracking Manoeuvering Aircraft by Interacting Multiple Model Filters,* C.R. of Bulg. Acad. of Sciences, Tome 49, No.1, pp.37-40, 1996.

[2] Bar-Shalom Y., Fortmann T., *Tracking and Data Association*, Academic Press, 1988.

[3] Bar-Shalom Y., *Multitarget-Multisensor Tracking: Advanced Applications*, Artech House,1990.

[4] Bar-Shalom Y., Li X.-R., *Estimation and Tracking : Principles, Techniques and software*, Artech House, 1993.

[5] Bar-Shalom Y., Li X.-R., *Multitarget-multisensor tracking:Principles and techniques*, YBS Editor, 1995.

[6] Bar-Shalom Y., Kirubarajan T., Gokberk C., *Tracking with classification-Aided Multiframe Data Association*, Proc. SPIE Conf. Signal and Data Proc. of Small Targets, Vol. 5204, San Diego, Aug. 2003.

[7] Blasch E., *Derivation of a Belief Filter for High Range Resolution Radar Simultaneous Target Tracking and Identification*, Ph.D. Thesis, Wright State Univ., 1999.

[8] Blasch E., Hong L., *Data Association through Fusion of Target Track and Identification Sets*, Proc. of Fusion 2000, Paris, July 2000.

[9] Blasch E., Connare T., Scarpino F., *Improving Track Attributes with Group Information Feedback*, Proc. of Fusion 2001 Int. Conf. on Inf. Fusion, Montréal, Canada, August 2001.

[10] Blasch E., Yang C., *Ten Methods to Fuse GMTI and HRRR Measurements for Joint Tracking and Identification*, Proc. of Fusion 2004, Stockholm, Sweden, July 2004.

[11] Blackman S., *Multitarget tracking with Radar Applications*, Artech House, 1986.

[12] Blackman S., Popoli R., *Design and Analysis of Modern Tracking Systems*, Artech House,1999.

[13] Bourgeois F., Lassalle J.C., *An Extension of the Munkres Algorithm for the Assignment Problem to Rectangular Matrices*, Com. of the ACM, Vol. 14, Dec. 1971, pp.802-806.

[14] Dezert J., *Vers un nouveau concept de navigation autonome d'engin. Un lien entre le PDAF et la Théorie de l'évidence*, Ph. D. Thesis, No. 1393, Orsay Univ., France, Sept. 1990.

[15] Dezert J., *Autonomous navigation with uncertain reference point using the PDAF*, Chap. 9 in Multitarget-Multisensor Tracking: Applications and Advances, Vol. 2, Y. Bar-Shalom Editor, Artech House, 1992..

[16] Florea M., *Dempster-Shafer evidence theory through the years : limitations, practical examples, variants under conflict and a new adaptive combination rule*, NATO - Advanced Study Institutes "Multisensor Data and Information Processing for Rapid and Robust Situation and Threat Assessment", Albena-Bulgaria 16-27 May 2005.

[17] Hwang I., *Air Traffic Surveillance and Control using Hybrid Estimation and Protocol-Based Conflict Resolution*, Ph.D. Thesis, Stanford University, 2003

[18] Hwang I., Balakrishnan H., Roy K., Shin J., Guibas L., Tomlin C., *Multiple-Target tracking and Identity Management Algorithm for Air Traffic Control*, Proc. of 2nd IEEE Sensors, Toronto, Canada, Oct. 2003.

[19] Hwang I., Balakrishnan H., Roy K., Tomlin C., *Multiple-Target tracking and Identity Management in Clutter, with Application to Aircraft Tracking*, Proc. of the AACC Am. Cont. Conf., Boston, MA, June 2004.

[20] Lerro D., Bar-Shalom Y., *Automated Tracking with Target Amplitude Information*, IEEE Trans. on AES, Vol.35, No.4, Oct.1999.

[21] Musso C., Dezert J., *Pistage et validation de piste par PDAF et reconnaissance*, Proc. of GRETSI, pp. 1089-1092, Juan Les Pins, France, Sept. 18-21, 1995.

[22] Popp R.L., Pattipati K.R., Bar-Shalom Y., *Dynamically Adaptable m-Best 2-D Assignment Algorithm and Multilevel Parallelization*, IEEE Trans.on AES, Vol. 35, No. 4, Oct.1999.

[23] Semerdjiev Tzv., Djerassi Em., Bojilov L., Konstantinova P., *Sensor Data Processing for Target Tracking. Algorithms and Applications*, (in Bulgarian), SoftTrade, 2006.

[24] Sentz K., Ferson S., *Combination of evidence in Dempster-Shafer Theory*, SANDIA Tech. Report, SAND 2002-0835, 96 pages, April 2002.

[25] Shafer G., *A Mathematical Theory of Evidence*, Princeton Univ. Press, NJ, 1976.

[26] Smarandache F., Dezert J. (Editors), *Applications and Advances of DSmT for Information Fusion (Collected Works)*, American Research Press, Rehoboth, 2004, http://www.gallup.unm.edu/~smarandache/DSmT-book1.pdf.

[27] Smarandache F., Dezert J., *Information Fusion Based on New Proportional Conflict Redistribution Rules*, in Proceedings of Fusion 2005 International Conference on Information Fusion, Philadelphia, July 2005.

[28] Smarandache F., Dezert J., *Proportional Conflict Redistribution Rules for Information Fusion*, see Chapter 1 in this volume.

[29] Tchamova A., Dezert J., Semerdjiev Tz., Konstantinova P., *Target Tracking with Generalized Data Association based on the General DSm Rule of Combination*, Proc. of Fusion 2004, Stockholm, Sweden, July, 2004.

[30] Tchamova A., Dezert J., Smarandache F., *A new class of fusion rules based on T-Conorm and T-Norm Fuzzy Operators*, International Journal Information & Security, Vol. 20, June 2006.

[31] Yang C., Bakich M., Blasch E., *Pose Angular-Aiding for Maneuvering Target Tracking*, in Proceedings of Fusion 2005 International Conference on Information Fusion, Philadelphia, July 2005.