Multitarget Tracking Applications of Dezert-Smarandache Theory

A. TCHAMOVA[1,2], J. DEZERT[3], T.SEMERDJIEV[1], P.KONSTANTINOVA[1]
[1]*Bulgarian Academy of Sciences, Institute for Parallel Processing,Sofia,Bulgaria*
[3]*Office National d'Etudes et Recherches Aérospatiales,Chatillon, France*

Abstract. The objective of this study is to present two multitarget tracking applications based on Dezert-Smarandache Theory (DSmT) for plausible and paradoxical reasoning: (1) Target Tracking in Cluttered Environment with Generalized Data Association incorporating the advanced concept of generalized data (kinematics and attribute) association to improve track maintenance performance in complicated situations (closely spaced and/or crossing targets), when kinematics data are insufficient for correct decision making.; (2) Estimation of Target Behavior Tendencies - it is developed on the principles of DSmT applied to conventional passive radar amplitude measurements, which serve as an evidence for corresponding decision-making procedures. The aim is to present and to approve the ability of DSmT to finalize successfully the decision-making process and to assure awareness about the tendencies of target behavior in case of discrepancies in measurements interpretation.

Keywords. Dezert-Smarandache Theory, Multitarget Tracking, Attribute Data Fusion, Generalized Data Association, Decision Making under Uncertainty.

Introduction

One important function of each radar surveillance system in cluttered environment is to keep and improve targets' tracks maintenance performance. It becomes a crucial and challenging problem especially in complicated situations of closely spaced and/or crossing targets. The design of a modern multitarget tracking (MTT) algorithm [4,5,6] in a real-life stressful environment motivates the incorporation of the advanced concepts for generalized data association. In order to resolve correlation ambiguities and to select the best observation-track pairings, in this first application of DSmT, a particular generalized data association approach is proposed and incorporated in a MTT algorithm. It allows the introduction of target attribute into the association logic, based on the general DSm rule of combination. Estimation of target behavior tendencies is an important subject related to angle-only tracking systems, which are based on passive sensors. These systems tend to be less precise than those based on active sensors, but

[1] Corresponding Author: Albena Tchamova, Bulgarian Academy of Sciences, Institute for Parallel Processing, "Acad. G.Bonchev"str.,bl.25-A,1113 Sofia, Bulgaria; e-mail: Tchamova@bas.bg.
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one important advantage is their vitality of being stealth. In a single sensor case only direction of the target as an axis is known, but the true target position and behavior (approaching or descending) remains unknown. A number of developed tracking techniques operating on angle-only measurements use additional information. We utilize the measured emitter's amplitude values in consecutive scans. This information can be used to assess tendencies in target's behavior and, consequently, to improve the overall angle-only tracking performance. The aim of this application is to present and to approve the ability of DSmT to finalize successfully the decision-making process and to assure awareness about the tendencies of target behavior in case of discrepancies of angle-only measurements. Results are presented and compared in details with the respective ones drawn from the fuzzy logic approach in companion papers [3,7]. The DSmT [1,2,3] proposes a new general mathematical framework for solving fusion problems. It overcomes the practical limitations of Dempster-Shafer Theory (DST), coming essentially from the acceptance of the third excluded middle. DSmT is an extension of probability theory and DST.

1. Target Tracking in Cluttered Environment with Generalized Data Association based on the General DSm Rule of Combination

1.1. Basic Elements of Tracking Process

The tracking process consists of two basic elements: data association and track filtering. The goal of the first element is to associate correctly observations to existing tracks. In order to eliminate unlikely observation-track pairing a validation gate is formed around the predicted track position. A measurements in the gate are candidates for association to the corresponding track. The used tracking filter is the first order extended Kalman filter [4,5]. We assume Gaussian distributed measurements. One defines a threshold constant for gate G such that correlation is allowed, if the relationship $d_{ij}^2 < G$ is satisfied , where d_{ij}^2 is the norm of residual vector.

1.2. Generalized Data Association

When attribute data are available, the generalized probability can be used to improve the assignment. In view of independence of the kinematic and attribute measurement errors, the generalized probability for measurement j originating from track i is:

$$P_{gen}(i,j) = P_k(i,j)P_a(i,j)$$

where $P_k(i,j)$ and $P_a(i,j)$ are kinematic and attribute probability terms. We choose a set of assignments that assures maximum of the total generalized probability sum, i.e. use the solution of the assignment problem $min\sum_{i=1}^{n}\sum_{j=1}^{m}a_{ij}\chi_{ij}$. Because our probabilities vary between 0 and 1, the elements of the particular assignment matrix are defined as : $a_{ij} = 1 - P_k(i,j).P_a(i,j)$ to satisfy the condition to be minimized.

1.3. The Fuzzification Interface

Fuzzification interface [3, pp.307] transforms crisp measurement into fuzzy set. The input variable is the Radar Cross Section (RCS) of the observed targets, which is determined as a linguistic variable. The modeled RCS data [7] are analyzed with the subsequent declaration for specified type (Fighter, Cargo) or False Alarms. Taking it in mind we define two frames of the problem: first- the ***size of RCS***: $\Theta_1 = \{VerySmall\ (VS), Small\ (S), Big\ (B)\}$ and second-the corresponding to it ***Target Type*** $\Theta_2 = \{FalseAlarms(FA), Fighter(F), Military\ C\arg o(C)\}$. The RCS for real targets is modelled as Swerling3, for False Alarm-as Swerling2 type functions.

1.4. Tracks' Updating Procedures

1.4.1 Using Classical DSm Rule of Combination

DSm classical combinational rule is used for tracks' updating:

$$m_{upd}^{ij}(C) = [m_{his}^{i} \oplus m_{mes}^{j}](C) =$$
$$= \sum_{A,B \in D^{\Theta_1}, A \cap B = C} m_{his}^{i}(A) . m_{mes}^{j}(B)$$

where $m_{upd}^{ij}(\ )$ represents the gbba of the updated track i with the new observation j; m_{his}^{i}, m_{mes}^{j} are respectively gbba vectors of track's i history and the new observation. DSmT takes into account and utilizes the paradoxical information hidden in nonempty intersections $VS \cap S \cap B, VS \cap S, VS \cap B, S \cap B$.

1.4.2. Using Hybrid DSm Rule of Combination

RCS data are used to analyze and subsequently to determine the type of the observed targets. Because of this it is maintained the second frame of the problem $\Theta_2 = \{(FA)lseAlarm, (F)ighter, Military(C)\arg o\}$. Doing this, we take in mind the following relationships:

If rcs is ***VerySmall*** *then* the target is ***False Alarm***
If rcs is ***Small*** *then* the target is ***Fighter***
If rcs is ***Big*** *then* the target is ***Cargo***

We transform the updated tracks' gbba from D^{Θ_1} into respective gbba in D^{Θ_2} ,i.e:

$$m_{upd}^{ij}(C_{C \in D^{\Theta_2}}) = m_{upd}^{ij}(C_{C \in D^{\Theta_1}})$$

Here the following exclusivity constraints are introduced:

$$FA \cap F \overset{M_1}{\equiv} \emptyset,\ FA \cap C \overset{M_1}{\equiv} \emptyset,\ F \cap C \overset{M_1}{\equiv} \emptyset,\ FA \cap F \cap C \overset{M_1}{\equiv} \emptyset .$$

We update the previous fusion result, obtained via the classical DSm rule with this new information on the model $M_1(\Theta_2)$. It is solved with the DSm hybrid rule [3], which transfers the mass of empty sets to the non-empty sets of D^{Θ_2}

1.5. The Generalized Data Association (GDA) Algorithm

We consider particular cluster and sets of n tracks and m received observations at a current scan. The validation test is used for filling the assignment matrix. We solve the assignment problem by the extension of Munkres algorithm [8]. The JPDA approach [4] is used to produce the probability terms P_k, P_a. To define the probabilities for data association the following steps are implemented : (1). Check gating ; (2). Clustering; (3). For each cluster: (3.1) Generate hypotheses following Depth First Search procedure; (3.2) Compute hypothesis probabilities for kinematic and attribute contributions; (3.3) Fill assignment matrix, solve assignment problem.

1.5.1. Attribute Probability Term for Generalized Data Association

The way of calculating the attribute probability term follows the joint probabilistic approach: $P''(H_l) = \prod_{i \neq 0,\, j \neq 0 \mid (i,j) \in H_l} d_e(i,j)$, where $d_e(i,j) = \sqrt{\sum_{C \in D^{\Theta_1}} \left(m^i(C) - m^j(C)\right)^2}$ is Euclidean distance between $m^i(C)$-predicted bba of C from track history of target i ; $m^j(C)$-bba of C of attribute measurement. The corresponding normalized probabilities are obtained as:

$$P_a(H_l) = \frac{P''(H_l)}{\sum_{l=1}^{N_H} P''(H_l)}$$

where N_H is the number of hypotheses. To compute $P_a'(i,j)$, a sum is taken over the probabilities from those hypotheses, in which this assignment occurs. Because the Euclidean distance is inverse proportional to the probability of association, the probability $P_a(i,j) = 1 - P_a'(i,j)$ is used to match the corresponding $P_k(i,j)$.

1.6. Simulation Scenario

Scenario 1 [3,pp.317] consists of two air targets (Fighter, Cargo) in clutter and a stationary sensor at the origin with T_{scan}= 5 sec., measurement standard deviations 0.3 [deg] and 60m for azimuth and range. The targets movement is from East to West with constant velocity of 250m/sec.. The headings of the fighter and cargo are 225 [deg] and 315 [deg] from North respectively. During the scan 11th –14th the targets perform maneuvers with 2.5g. Scenario 2 [3,pp.317] consists in four air targets (alternating Fighter, Cargo, Fighter, Cargo) moving with constant velocity of 100m/sec. The heading at the beginning is 155 [deg] from North. The targets make maneuvers with 0.85g-(right, left , right turns).

1.7. Comparative Analysis of the Results obtained using Kinematics only, Dezert-Smarandache and Dempster-Shafer Theory

The incorporated advanced concept of GDA leads to improving of the tracks' maintenance performance especially in complicated situations (closely spaced and/or crossing targets). It influences over the obtained tracks' purity results [3, pp.318-321]. The tracks' purity in case of using DSmT increases in comparison with the obtained one via DST. Analyzing all the obstacles, it can be underlined that :

- DSmT makes possible to process and utilize flexibly the paradoxical information - case, which is peculiar to the problem of multiple target tracking in clutter, when the conflicts between the bodies of evidence often become high and critical. That way it contributes to a better understanding of the overall tracking situation and to producing an adequate decision. Processing the paradoxes, the estimated entropy in the confirmed tracks' attribute histories decreases during the consecutive scans.
- Because of the Swerling type modelling, the observations for False Alarms, Fighter and Cargo are too much mixed. That fact causes some conflicts between general basic beliefs assignments of the described bodies of evidence. When the conflict becomes unity, it leads to indefiniteness in Dempster's rule and consequently the fusion process can not be realized and the whole MTT corrupts.
- If the new measurement leads to track's attribute update, in which some particular hypothesis is supported by the unity, after that point on, the Dempster's rule becomes indifferent to any other measurements in the next scans. It means the track's attribute history remains the same, regardless of the received observations. It leads to non coherent and non adequate decisions according to the right associations.

2. Estimation of Target Behavior Tendencies using DSmT.

2.1. Approach for Behavior Tendency Estimation

The block diagram of the target's behavior tracking system [3, pp.291] maintains two single-model-based Kalman-like filters in parallel using two models of target behavior - ***Approaching*** and ***Receding***. The tendency prediction is based on Zadeh's compositional rule [9,10,11]. The updating procedure uses DSm rule to estimate target behavior states.

2.2. .Fuzzification Interface

A decisive variable in our task is the transmitted from the emitter amplitude value, received at consecutive time moments. We use the fuzzification interface [3, pp.292] that maps it into two fuzzy sets $\theta = \{Small = S, Big = B\}$. Their membership functions rely on the inverse proportion dependency between the measured amplitude value and corresponding distance to target.

2.3 Behavior Models

We consider two models of target behavior: ***Approaching*** - characterized as a stable process of gradually amplitude value increasing; ***Receding*** - characterized as a stable process of gradually amplitude value decreasing. To comprise appropriately these models the following rule bases have to be carried out:

Behavior Model 1: Approaching Target:	**Behavior Model 2: Receding Target**:
Rule 1: *IF* $A(k)$ *is Small THEN* $A(k+1)$ *is Small*	**Rule 1**: *IF* $A(k)$ *is Big THEN* $A(k+1)$ *is Big*

Rule 2: *IF* $A(k)$ *is Small THEN* $A(k+1)$ *is Big* **Rule 2**: *IF* $A(k)$ *is Big THEN* $A(k+1)$ *is Small*

Rule 3: *IF* $A(k)$ *is Big THEN* $A(k+1)$ *is Big* **Rule 3***: IF* $A(k)$ *is Small THEN* $A(k+1)$ *is Small*

The models are derived as fuzzy graphs, in which Larsen product operator is used for fuzzy conjunction ; maximum for fuzzy union ; Zadeh max-min rule of composition [14]

Relation1: Approaching Target

$k \to k+1$	S	$S \cap B$	B	$S \cup B$
S	1	0	1	0
$S \cap B$	0	0	0	0
B	0.2	0	1	0
$S \cup B$	0	0	0	0

Relation2: RecedingTarget

$k \to k+1$	S	$S \cap B$	B	$S \cup B$
S	1	0	0.2	0
$S \cap B$	0	0	0	0
B	1	0	1	0
$S \cup B$	0	0	0	0

2.4 Models' Conditioned Attribute State Prediction

At initial time moment k the target is characterized by the fuzzified amplitude state estimates according to the models $\mu_{A^{App}}(k/k)$ and $\mu_{A^{\mathrm{Re}c}}(k/k)$. Using them and applying Zadeh max-min compositional rule to relations 1 and 2 we obtain models' conditioned amplitude state predictions for time moment $k+1$, i.e.:

$$\mu_{A^{App}}(k+1/k) = \max\left(\min\left(\mu_{A^{App}}(k/k), \mu_{App}(k \to k+1)\right)\right)$$

$$\mu_{A^{\mathrm{Re}c}}(k+1/k) = \max\left(\min\left(\mu_{A^{\mathrm{Re}cp}}(k/k), \mu_{\mathrm{Re}c}(k \to k+1)\right)\right)$$

2.4 Attribute State Updating using DSmT

The updating procedure uses DSm combinational rule:

$$m_{upd}^{App/\mathrm{Re}c}(C) = \left[m_{pred}^{App/\mathrm{Re}c} \otimes m_{mes}\right](C) =$$

$$= \sum_{A,B \in D^{\theta}, A \cap B = C} m_{pred}^{App/\mathrm{Re}c}(A).m_{mes}(B)$$

DSmT takes into account and utilize the paradoxical information hidden in nonempty set $S \cap B$. It relates to the case, when the moving target resides in an overlapping region, when it is hard to predict properly the tendency in its behavior.

2.4. The Decision Criteria

The decision criterion for estimation the plausibility of models is based on the evolution of generalized pignistic entropies [3], associated with updated amplitude states: $H_{pig}^{M}\left(P_{upd}^{M}\right)=-\sum_{A\in\nu}P_{upd}^{M}\{A\}\ln\left(P_{upd}^{M}\{A\}\right)$.The correct model corresponds to the smallest entropy value among these entropies.

2.5 Simulation Study

A simulation scenario [3, pp.296] is developed for a single target trajectory in plane coordinates and for constant velocity movement. The target's start-point and velocities are: $\left(X_0=5km, Y_0=10km\right)$, $\dot{X}=100m/s, \dot{Y}=100m/s$, $\dot{X}=-100m/s, \dot{Y}=-100m/s$ The time sampling rate is $T=10s$. The measured amplitude value is a random Gaussian distributed process.

2.6 Comparison between result of DSmT and Fuzzy Logic (FL) Approaches

DSmT and FL approaches deal with a frame of discernments, based in general on imprecise/vague notions and concepts . DSmT allows to deal with rational, uncertain or paradoxical data, operating on the HyperPower Set. In our particular application DSmT gives an opportunity for flexible tracking during the overlapping region $S\cap B$.DSmT based behavior estimates can be characterized as a noise resistant, while FL uses an additional noise reduction procedure to produce 'smoothed' behavior estimates.

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