Target Identification based on DSmT

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Abstract. An approach providing fast reduction of the full ignorance in the target identification process is proposed. It uses the new Dezert-Smarandache theory (DSmT) for plausible and paradoxical reasoning, combined with fuzzy set theory. The approach utilizes the information from the adjoint sensor and the additional information obtained from a priori defined objective and subjective considerations. As a result the pignistic probabilities for target's nature are obtained and analyzed.

Keywords. Target Identification, Dezert-Smarandache Theory, DSmT, Fuzzy Logic, Attribute Data Fusion

Introduction

The process of a target state recognition by an IFF (Identification Friend/Foe) sensor is considered. The information received from it concerns a single attribute: 'friend target' ('F'). The absence of evidence (so-called response) however, does not a priori ensure 100% reliability for the hypothesis 'hostile target' ('H') and a problem of the possible wrong target recognition arises. This problem is especially complicated when there is no ability to postpone the moment of decision-making. In this case the full ignorance makes the support as well as the probability for alternative hypotheses 'friend target' or 'hostile target' equally ambiguous and plausible. As a result, the alternative decisions made on that basis lead to equal degree of risk. One-way out of the described problem is to incorporate additional attribute information at the different level of abstraction from another, disparate sensor [1,2]. Because of that reason the IFF sensor is often adjoined with radar or infrared sensor (IRS). The evidence from the additional sensor should clarify this dilemma. Unfortunately, this information does not always give an implicit answer at the moment of question (because of the sensors' technical particularities). A more expensive solution is to increase the number of additional sensors [1]. In the paper an approach, combining DSmT [3,4] and fuzzy sets theory [5,6] is applied in order to utilize all available information - the a priori defined objective and subjective considerations, concerning relationships between the attribute

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components at different levels of abstraction and the attribute information from the adjoint sensor (radar).

1. Dezert-Smarandache Theory

The DSmT of plausible and paradoxical reasoning [3,4] proposes a new general mathematical framework for solving fusion problems. This theory overcomes the practical limitations of the Dempster-Shafer theory (DST) [7], coming essentially from its inherent constraints, which are closely related with the acceptance of the law of the third excluded middle. The foundations of DSmT is to refute that law and to allow imprecise/vague notions and concepts between elements of the frame of the problem Θ. It can be interpreted as a general and direct extension of probability theory and DST.

1.1. Free Dezert-Smarandache Model

Let $\Theta = \{\theta_1, ...\theta_n\}$ be a set of n elements, which cannot be precisely defined and separated. A free-DSm model, denoted as $M^f(\Theta)$, consists in assuming that all elements $\theta_i, i = 1,...,n$ of Θ are not exclusive. The free-DSm model is an opposite to the Shafer's model $M^0(\Theta)$, which requires the exclusivity and exhaustivity of all elements $\theta_i, i = 1,...,n$ of Θ.

1.2. Definition of Hyper-Power Set and Classical DSm Rule of Combination

The hyper-power set D^θ is defined as the set of all composite possibilities build from Θ with $\cup$ and $\cap$ operators such that:

1. $\emptyset, \theta_1, ...\theta_n \in D^\Theta$
2. $\forall A \in D^\theta, B \in D^\theta, (A \cup B) \in D^\theta, (A \cap B) \in D^\theta$.
3. No other elements belong to D^Θ, except those, obtained by using rules 1 or 2.

From a general frame of discernment Θ with its free-DSm model, it is defined a map $m(.): D^\theta \to [0,1]$, associated to a given source of evidence, which can support paradoxical, or conflicting information, as follows: $m(\emptyset) = 0$ and $\sum_{A \in D^\theta} m(A) = 1$

The quantity $m(A)$ is called A's general basic belief assignment (gbba) or the general basic belief mass for A. The belief and plausibility functions are defined for $\forall A \in D^\theta$:

$$Bel(A) = \sum_{B \in D^\theta, B \subseteq A} m(B) \; ; \qquad Pl(A) = \sum_{B \in D^\theta, B \cap A \neq \emptyset} m(B)$$

The DSm classical rule of combination (DSmC) is based on the free-DSm model. For $k \geq 2$ independent bodies of evidence with gbbas $m_1(.)$, $m_2(.)$, …, $m_k(.)$:

$$m_{M^f(\Theta)}(A) = \sum_{\substack{X_1 ... X_k \in D^\Theta \\ X_1 \cap ... \cap X_k = A}} \prod_{i=1}^{k} m_i(X_i) \qquad (1)$$

with $m_{\mathrm{M}^f(\Theta)}(\varnothing)=0$ by definition. This rule is commutative and associative and requires no normalization procedure.

1.3. Definition of DSm Hybrid Model

A DSm hybrid model $\mathrm{M}(\Theta)$ [4] is defined from the free-DSm model $\mathrm{M}^f(\Theta)$ by introducing integrity constraints on some elements $A \in D^\Theta$ in accordance with the exact nature of the problem. An integrity constraint on $A \in D^\Theta$ consists in forcing $A \overset{\mathrm{M}}{\equiv} \varnothing$ through the model. The Shafer's model $\mathrm{M}^0(\Theta)$ can be considered as the most constrained free DSm model.

1.4. DSm Rule of Combination for Hybrid Model

The DSm hybrid rule of combination (DSmH), associated to a given DSm hybrid model $\mathrm{M} \neq \mathrm{M}_\varnothing$, for $k \geq 2$ independent sources of evidence is defined for all $A \in D^\Theta$ as:

$$m_{\mathrm{M}(\Theta)}(A)=\phi(A)[S_1(A)+S_2(A)+S_3(A)] \tag{2}$$

where $\phi(A)$ is the characteristic non-emptiness function of set A, i.e. $\phi(A)=1$ *if* $A \notin \varnothing$ and $\phi(A)=0$ otherwise. Here:

$S_1(A)=\sum_{\substack{X_1,X_2,\dots X_k \in D^\Theta \\ X_1\cap X_2\cap\dots\cap X_k=A}} \prod_{i=1}^{k} m_i(X_i)$ corresponds to the DSmC ;

$S_2(A)=\sum_{\substack{X_1,X_2,\dots X_k \in \varnothing \\ [U=A]\vee[(U\in\varnothing)\wedge(A=I_t)]}} \prod_{i=1}^{k} m_i(X_i)$ represents the mass of all relatively and absolutely empty sets, which are transferred to the total or relative ignorance:

$S_3(A)=\sum_{\substack{X_1,X_2,\dots X_k \in D^\Theta \\ X_1\cap X_2\cap\dots\cap X_k\in\varnothing \\ X_1\cup X_2\cup\dots X_k=A}} \prod_{i=1}^{k} m_i(X_i)$ transfers the sum of relatively empty sets to the non-empty sets.

2. Approach Description

2.1. The a Priori Data Base Definition

The a priori database is realized as a fuzzy relation. It takes into account the defined *objective considerations*, connecting some attributes' components expressed at different levels of abstraction (for example the fuzzy relation '*target's type* - *target's nature*'). For that purpose it is defined:

- the set $X = D^\theta = \{x_1, x_2, \dots, x_{2^{2^n}-1}\}$, corresponding to the hyper-power set D^θ, related to the level of abstraction of the adjoint sensor (the objects' types

$O_i ,i = 1,2,...,n$). Because the objects' types are exclusive, here the Shafer's model is valid and the hyper-power set is reduced to Dempster-Shafer (DS) power set:
$x_1 = O_1; x_2 = O_2 ;...; x_n = O_n , x_{n+1} = O_1 \cup O_2 ;...,\ x_{2^n-1} = O_1 \cup O_2 \cup ... \cup O_n$

- the set Y, corresponding to the level of abstraction of the base sensor ($Y = \{y_1 = F(riend), y_2 = H(ostile)\}$);
- the matrix $R : X \to Y$ is a fuzzy relation with membership function (MF): $\mu_R(x_k , y_l) \in [0,1]$; $k = 1,2,...,2^n - 1$; $l = 1,2$, where n is the number of considered target types. The conditions MF has to satisfy according to the DSmT are:

$$\mu_R(x_k , y_l) \geq 0 ; \quad \sum_{k=1}^{2^n-1} \mu_R(x_k , y_l) = 1, l = 1,2 .$$

2.2. Semantic Transformation

The information granule m_X, concerning object's type is transformed in a corresponding fuzzy set S_X: $\mu_{S_X}(x_k) = m_X(x_k), k = 1,...,(2^n - 1.)$.

2.3. Application of Zadeh' Compositional Rule

The image of the fuzzy set S_X through the mapping R is received. The output fuzzy set T_Y concerns the target's nature with:

$$\mu_{T_Y}(y_l) = \sup_{x_k \in X} \{min[\mu_R(y_l , x_k), \mu_{S_X}(x_k)]\}.$$

T_Y represents the extracted from the measurement *non-implicit* attribute information.

2.4. Inverse Semantic Transformation

The fuzzy set T_Y is transformed to an information granule m_{Y_R} through normalization of membership values with respect to the unity interval.

2.5. Application of DSm Hybrid Rule of Combination

The DSmH (2) is used to combine two evidences: m_X and m_{Y_R}**.** This aggregation reduces the full ignorance in regard to the target's nature immediately.

2.6. Decision Making based on Pignistic Probabilities

Generalized Pignistic Transformation[4] is used here in order to take a rational decision about the target's nature within the DSmT framework:

$$P\{A\} = \sum_{X \in D^\theta} \frac{C_M(X \cap A)}{C_M(X)} m(X) \quad \text{for } \forall A \in D^\theta \qquad (3)$$

The decision is taken by the maximum of pignistic probability function $P\{.\}$

3. Simulation Scenario and Results

Two sensors are available: radar and an IFF-sensor. Their evidences are formed, defining a frame of discernments about the target's type: $\Theta = \{O_1, O_2, O_3\}$, O_1-'*fighter*', O_2-'*airlift cargo*', O_3-'*bomber*', and about the target nature: $H \subset \{O_1, O_3\}$, $F \subset \{O_2\}$. The corresponding to these target's types attribute components are the angular sizes A of the targets' blips, measured on the radar screen. To define the influence of these components on the considered problem it is sufficient to know the specific features of their probabilistic 'behavior' to describe them in fuzzy way. It is supposed that: the average $\overline{A}_1$ of the angular size A_1, corresponding to O_1 is the minimal one($\overline{A}_1$ depends on the size of the elementary radar's volume A_V); $P(A_1 > A_V) \approx 0$; $\overline{A}_2$, corresponding to O_2, is the maximal one; $P(A_2 < A_V) \approx 0$; $\overline{A}_3$ for O_3, obeys to the relation $\overline{A}_1 < \overline{A}_3 < \overline{A}_2$; $P(A_3 < A_V), P(A_3 > A_2)$ can not be neglected.

The *worst case*: when *a hostile target is observed* and the obtained respective radar blip has a medium angular size. It can originate from target related to any type, i.e. $\theta = \theta_1 \cup \theta_2 \cup \theta_3$. The information granule is defined as:

$$m_X = \{m_X(\theta_1) = 0.2, \quad m_X(\theta_2) = 0.2 \quad m_X(\theta_3) = 0.3 \quad m_X(\theta_i \cup \theta_j) = 0.0 \quad m_X(\Theta) = 0.3\}$$

The worst evidence is obtained from the IFF-sensor (the IFF sensor has not received a response from the observed target): $m_Y = \{m_Y(F) = 0, \quad m_Y(H) = 0, \quad m_Y(\Theta) = 1\}$.

If the DSmC $(m_X \oplus m_Y)$ is used to fuse these two evidences, the result will not change the target nature estimate, because of the effect of vacuous belief assignment.

Step 4.1: For the considered example, the sets X and Y are:

$$X = \{O_1, O_2, O_3, O_1 \cup O_2, O_1 \cup O_3, O_2 \cup O_3, \Theta\}, Y = \{F, H\}.$$

The a priori defined relation $R: X \to Y$ (data base) is described in the table below:

R	$y_1 = F$	$y_2 = H$
$x_1 = O_1$	$\mu_R(O_1, F) = 0$	$\mu_R(O_1, H) = 0.3$
$x_2 = O_2$	$\mu_R(O_2, F) = 0.8$	$\mu_R(O_2, H) = 0.3$
$x_3 = O_3$	$\mu_R(O_3, F) = 0$	$\mu_R(O_3, H) = 0.3$
…	0	0
$x_5 = \Theta$	$\mu_R(\Theta, F) = 0.2$	$\mu_R(\Theta, H) = 0.1$

It takes into account the *a priori* defined objective considerations. Here it is presumed that the information obtained from some particular schedule of civilian and military aircraft's flights, excludes flights of friendly fighters and bombers, but allows planned flights of friendly civil passenger aircrafts and of friendly military airlift operations.

Step 4.2: The evidence from the radar sensor m_X is transformed in a fuzzy set S_X :

Step 4.3: Define the image of the fuzzy set S_X through the mapping R. It is the fuzzy set T_Y, concerning the nature of the target with $\mu_{T_Y}(y_1) = 0.2$ and $\mu_{T_Y}(y_2) = 0.3$.

Step 4.4: Normalization step: $m_{Y_R} = \{m_{Y_R}(F) = 0.4, \quad m_{Y_R}(H) = 06\}$. m_{Y_R} contains the non-implicit information about the target nature in the radar measurement.

Step 4.5: DSmC (1) is used to combine the evidences m_X and m_{Y_R} :

	$m_{Y_R}(F = O_2) = 0.4$	$m_{Y_R}(H = O_1 \cup O_3) = 0.6$
$m_X(O_1) = 0.2$	$m(O_1 \cap O_2) = 0.08$	$m(O_1) = 0.12$
$m_X(O_2) = 0.2$	$m(O_2) = 0.08$	$m(F \cap H) = 0.12$
$m_X(O_3) = 0.3$	$m(O_2 \cap O_3) = 0.12$	$m(O_3) = 0.18$
$m_X(\Theta) = 0.3$	$m(O_2) = 0.12$	$m(H) = 0.18$

According to the true nature of the problem, here the following integrity constraints are introduced: $O_1 \cap O_2 = \varnothing$, $O_2 \cap O_3 = \varnothing$, $F \cap H = \varnothing$. Applying DSmH(2), the updated vector of probability masses m_{upd} is obtained below:

$$\left\{ \begin{matrix} m_{upd}(O_1) = 0.12 & m_{upd}(O_2) = 0.2 & m_{upd}(O_3) = 0.18 & m_{upd}(H) = 0.18 \\ m_{upd}(O_1 \cup O_2) = 0.08 & m_{upd}(O_2 \cup O_3) = 0.12 & m_{upd}(F \cup H) = 0.12 & \end{matrix} \right\}$$

Step 4.6: In conclusion, the pignistic probabilities (3) are calculated in order to make decisions about target's nature: $P(H) = 0.66, P(F) = 0.34$. The other pignistic probabilities of interest are: $P(O_1) = 0.29, P(O_3) = 0.37$. It is obvious, that the evidence, supporting propositions '*target type is* O_1 ' and '*target type is* O_3 ' enhance the support for the proposition '*H'*. But the evidence for target being '*H'* does not enhance the support for proposition '*target type is* O_1 ' or '*target type is* O_3 '.

For completeness of this study two other possible radar measurements are considered here. They concern the cases of measured target type '*fighter'* (and related to it '*bomber'*) or '*airlift cargo'* (and related to it '*bomber'*):

$$m'_X = \{m_X(O_1) = 0.3 \quad m_X(O_2) = 0.2 \quad m_X(O_3) = 0.2 \quad m_X(O_1 \cup O_3) = 0.3 \quad m_X(\Theta) = 0\}$$
$$m''_X = \{m_X(O_1) = 0.2 \quad m_X(O_2) = 0.3 \quad m_X(O_3) = 0.2 \quad m_X(O_2 \cup O_3) = 0.3 \quad m_X(\Theta) = 0\}$$

The measurement m'_X supports *hostile fighter'*, additionally increasing the pignistic probability $P(H) = 0.84$ and decreasing $P(F) = 0.16$ .The measurement m''_X supports *a friend's airlift cargo'* additionally increasing the pignistic probability $P(F) = 0.38$ and decreasing $P(H) = 0.62$. It can be noted that the both probabilities become very close, because of the lack of more categorical evidence supporting '*H'*. The existing small difference between them is due to the ambiguous evidence $O_2 \cup O_3$. Another confirmation of the proposed approach benefits is to compare the results with these, obtained by direct utilization of the mentioned database and DSmH. For this purpose the database is considered as consisting of two separate data basis (m_{DB}^H and m_{DB}^F) concerning the propositions '*F'* and '*H'* respectively. Each database contains two columns (1,2 and 1,3 respectively). These granules can be used for direct updating of m_X to check the both alternatives: $m_X \otimes m_{DB}^{H} = m_{upd}^{H}$, $m_X \otimes m_{DB}^{F} = m_{upd}^{F}$. The pignistic probabilities obtained for the both alternatives are:

$$P_{upd}^{H}(H) = 0.685,\; P_{upd}^{H}(F) = 0.315;\; P_{upd}^{F}(H) = 0.34,\; P_{upd}^{F}(F) = 0.66 .$$

The obtained probabilities that way show some improvement of the initial full ignorance, but it is not sufficient for practical needs due to the high similarity of the both results ($P_{upd}^{H}(H) = 0.685$, $P_{upd}^{F}(F) = 0.66$).

The future investigations, in order to find the way-out of that problem is the application of the new advanced Proportional Conflict Redistribution Rules (especially PCR5) [8] which proportionally redistribute the conflicting mass (total or partial) to non-empty sets according to all integrity constraints using a given strategy.

4. Conclusions

The new Dezert-Smarandache theory for plausible and paradoxical reasoning is used for reduction of the full ignorance in the process of target identification. Combined with fuzzy set theory, it utilizes the information from the adjoint sensor and the additional information obtained from *a priori* defined objective and subjective considerations. DsmT allows the fusion of sources on free-DSm model and on any more complex/restricted one, like the Shafer's model. It can successfully deal with the cases, when the conflict between the sources becomes high. The decision-making process is based on the generalized pignistic transformation. It allows building and analyzing the pignistic probabilities for target's nature *{Friend, Hostile}*. The generated output results simultaneously take into account all available information concerning the considered stochastic events in the database.

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