Albena Tchamova, Jean Dezert, Florentin Smarandache

Object identification using T-conorm/norm fusion rule

Albena Tchamova[1]
IPP, Bulgarian Academy of Sciences,
"Acad. G. Bonchev" Str., bl. 25-A,
1113 Sofia, Bulgaria.
tchamova@bas.bg

Jean Dezert
ONERA/DTIM/SIF,
29 Avenue de la Division Leclerc,
92320 Châtillon, France.
jean.dezert@onera.fr

Florentin Smarandache
Chair of Math. & Sciences Dept.,
University of New Mexico,200 College Road,
Gallup, NM 87301, U.S.A.
smarand@unm.edu

Published in:
Florentin Smarandache & Jean Dezert (Editors)
Advances and Applications of DSmT for Information Fusion
(Collected works), Vol. III
American Research Press (ARP), Rehoboth, 2009
ISBN-10: 1-59973-073-1
ISBN-13: 978-1-59973-073-8
Chapter XX, pp. 519 - 527

Abstract: *This small chapter presents an approach providing fast reduction of total ignorance in the process of target identification. It utilizes the recently defined fusion rule based on fuzzy T-conorm/T-norm operators, as well as all the available information from the adjoint sensor and additional information obtained from the a priori defined objective and subjective considerations, concerning relationships between the attribute components at different levels of abstraction. The approach performance is estimated on the base of the pignistic probabilities according to the nature of the objects considered here. The method shows better efficiency in comparison to the pure Dempster-Shafer theory based approach. It also allows to avoid the application of the Bayesian principle of indifference and improves the separation power of the decision process.*

1 - This work is partially supported by MONT grant MI-1506/05.

20.1 Introduction

Object identification is an important problem of considerable interest to many civilian and military sectors. In this chapter the process of object state recognition by an IFF (Identification Friend/Foe) sensor is examined. The information received from the sensor pertains to a single attribute: *'friend target' (F)*. The absence of evidence (so-called response), however, does not a priori ensure 100 percents reliability for the hypothesis *'hostile target'(H)* and the problem of possible wrong target recognition arises. This problem is especially complicated when the moment of decision-making cannot be postponed. In this case, the total ignorance presence renders the probability of alternative hypotheses of *'friendly target'* or *'hostile target'* equally ambiguous and plausible. As a result, alternative decisions made on this basis pose an equal degree of risk. From the point of view of Dempster-Shafer theory (DST) [2, 4, 9], the proposition ought to be supported is: *'an availability of full ignorance'*, i.e. $m(\Theta) = 1$. In Bayesian theory [1], according to the principle of indifference, this problem is handled by setting equal a priori probabilities to each alternative hypothesis. One way out of the described problem is to incorporate additional attribute information at a different level of abstraction from another disparate sensor [3, 5, 14]. For this reason, the IFF sensor is often adjoined with a radar or infrared sensor (IRS). Evidence from the additional sensor should help to resolve this dilemma. The measurement coordinates originating from a target moving in an air-traffic corridor is an example for such evidence. The measurement's spatial and spectral signal parameters are another example. Unfortunately, this information does not always provide an implicit answer at the time the question is posed (due to the sensors' technical particularities). A more expensive solution is to increase the number of sensors [3], but this often leads to increased conflicts between them. In such cases Dempster's rule yields unfortunately unexpected, counter-intuitive results [11].

In this work, one utilizes a new class of fusion rules introduced in [13] in the framework of Dezert-Smarandache Theory (DSmT) of plausible and paradoxical reasoning [11, 12]. Our approach is based on fuzzy T-conorm/T-norm operators and on all the available information - from the adjoint sensor (radar) and additional information obtained from a priori defined objective and subjective considerations concerning relationships between the attribute components at different levels of abstraction. In the next section we present briefly the main principles of fuzzy based T-Conorm/Norm (TCN) fusion rule. Then the proposed approach for object identification is described, tested and evaluated. Concluding remarks are given in the last section.

20.2 Approach description

- *The a priori dataBase definition.* The a priori database is realized as a fuzzy relation [7]. It takes into account the defined objective considerations connecting the components of some attributes expressed at different levels of abstraction (for example the fuzzy relation *'target type - target nature'*). For this purpose, it is defined:

- The set $X = \{x_1, x_2, ...x_{2^n-1}\}$, relating to the level of abstraction of the adjoint sensor (the object type $O_i, i = 1, 2, ..., n$) corresponds to the Dempster-Shafer Theory power set 2^Θ.

$$x_1 = O_1, x_2 = O_2, ..., X_n = O_n$$
$$x_{n+1} = O_1 \cup O_2, ...$$
$$x_{2^n-1} = O_1 \cup O_2 \cup ... \cup O_n$$

- The set Y corresponds to the level of abstraction of the base sensor ($Y = \{y_1 = \mathbf{F}(riend), y_2 = \mathbf{H}(ostile)\ )$.
- The matrix $R : X \Rightarrow Y$ is a fuzzy relation with a 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 object's types. The conditions that MF must satisfy according to the DSmT and DST are:

$$\sum_{k=1}^{2^n-1} \mu_R(x_k, y_l) = 1, l = 1, 2$$

- *Semantic transformation.* The information granule m_X pertaining to the object's type is transformed in a corresponding fuzzy set S_X:

$$\mu_{S_X}(x_k) = m_X(x_k), k = 1, ..., (2^n - 1)$$

- *Application of Zadeh's compositional rule.* The image of the fuzzy set S_X through the particular mapping [15–17] is received. The output fuzzy set T_Y corresponds to the target's nature by means of:

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

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

- *Inverse semantic transformation.* The fuzzy set T_Y is transformed into an information granule m_{Y_R} through a normalization of membership values with respect to the unity interval.

- *Application of the TCN rule of combination.* The TCN fusion rule introduced in [13] is described in section 15.5 of chapter 15 in this book and therefore it will not be presented in details here. It is used to combine two evidences: $m_X(.)$ and m_{Y_R}. This aggregation immediately reduces the total ignorance with regard to the target's nature.

- *Decision making based on the pignistic probabilities.* The Generalized Pignistic Transformation [11] is used to take a rational decision about the target's nature within the DSmT framework:

$$P\{A\} = \sum_{X \in D^\Theta} \frac{C_M(X \cap A)}{C_M(X)}.m(X), \forall A \in D^\Theta$$

  The decision is taken by the maximum of the pignistic probability function P.

20.3 Simulation scenario and results

Sensor evidence defines a frame of discernment for the target's type: $\Theta = O_1, O_2, O_3$, where object O_1 means 'fighter', O_2 means 'airlift cargo', O_3 means 'bomber', and the target's nature: $H \subset O_1, O_3$ (Hostile) , $F \subset O_2$ (Friend). The attribute components corresponding to these objects' types are the angular sizes A of objects' blips measured on the radar screen. In order to define the influence of these components on this problem, it is sufficient to know the specific features of their probabilistic 'behavior' and to assign fuzzy values to them. It is supposed that:

- the average $\bar{A}_1$ of the angular size A_1 corresponding to O_1 is the minimal value ($\bar{A}_1$ depends on the size of the elementary radar's volume A_V);
- the probability of the event this angular size will exceed the elementary radar's volume can be neglected (i.e. $P(A_1 > A_V) \approx 0$);
- the average $\bar{A}_2$ of the angular size A_2, corresponding to target O_2 is the maximal one;
- the probability of the event that some realization of this stochastic variable A_2 will be lower than the angular size of the elementary radar's volume A_V can be neglected too (i.e.$P(A_2 < A_V) \approx 0$);
- the average $\bar{A}_3$ of the angular size A_3 , corresponding to the target O_3, obeys to the relation $\bar{A}_1 < \bar{A}_3 < \bar{A}_2$;
- the probabilities $P(A_3 < A_V)$, $P(A_3 > A_2)$ cannot be neglected.

The worst case is when a hostile target is observed and the obtained respective radar blip has a medium angular size. It can originate from a target of any type, i.e. $\Theta = O_1 \cup O_2 \cup O_3$. This is the case, when the approach proposed here demonstrates its advantages in comparison with the DST based approach. The information granule is defined as:

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

Also, the 'worst' evidence is obtained from the IFF-sensor (it has not received a response from the observed target):

$$\mathbf{m}_Y = \{m_Y(F) = 0 \quad m_Y(H) = 0 \quad m_Y(\Theta) = 1.0\}$$

If the DS rule of combination ($\mathbf{m}_X \oplus \mathbf{m}_Y$) is used to fuse these two sources of evidence, the result will not change the target nature estimate because of the effect of vacuous belief assignment.

- *Step 1.* For the considered example, the sets X and Y are:

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

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

Table 20.1: Fuzzy relation for the database definition.

The a priori defined relation $R : X \Rightarrow Y$ (the particular database) is described in Table 20.1.

This relation is not arbitrarily chosen [10]. It is presumed that the information obtained from some particular schedule of civilian and military aircraft flights excludes flights of friendly fighters and bombers but allows planned flights of friendly civil passenger aircrafts and friendly military airlift operations. It is possible (but as it follows from the example, it is not recommendable) to make general inferences by using only this a priory information, because of the significant cost of the wrong decision *'target is friend'*.

On the other hand, the uncertainty with respect to the hostile intentions imposes an equal distribution of the probabilities, concerning propositions for:

- a reconnaissance mission performed by a hostile fighter;
- an assault dropped by a hostile cargo aircraft;
- a strike mission performed by a hostile bomber.

Obviously, it is not realistic to expect an appearance of hostile targets, while the proposition for the alternative event possesses a high degree of probability

- *Step 2.* The evidence $\mathbf{m}_X$ from the radar sensor is transformed in a fuzzy set S_X.

- *Step 3.* The image T_Y of the fuzzy set S_X, defined through the mapping $\boldsymbol{R}$ infers an information concerning target's nature as follows:

$$\mu_{T_Y}(y_1 = F) = 0.2 \quad \mu_{T_Y}(y_2 = H) = 0.3$$

- *Step 4.* The normalization procedure yields:

$$\mu_{T_Y}(y_1 = F) = 0.4 \quad \mu_{T_Y}(y_2 = H) = 0.6$$

It contains the non-implicit information about the target's nature in the radar measurement.

- *Step 5.* TCN fusion rule is used to combine the evidence $\mathbf{m}_X$ and $\mathbf{m}_{Y_R}$. In accordance with the true nature of the problem (Shafer's model), the following integrity constraints are introduced:

$$O_1 \cap O_2 = \emptyset, \quad O_2 \cap O_3 = \emptyset, \quad O_1 \cap O_3 = \emptyset, \quad F \cap H = \emptyset$$

The conjunction of propositions gives:

$$O_1 \cap F = O_1 \cap O_2 = \emptyset$$

$$O_2 \cap F = O_2 \cap O_2 = O_2$$

$$O_3 \cap F = O_3 \cap O_2 = \emptyset$$

$$\Theta \cap F = O_2$$

$$O_1 \cap H = O_1$$

$$O_2 \cap H = F \cap H = \emptyset$$

$$O_3 \cap H = O_3$$

$$\Theta \cap H = H$$

By applying TCN fusion rule, the updated vector of masses of belief $\tilde{\mathbf{m}}_{upd}(.)$ concerning both levels of abstraction (target's type and target's nature) is obtained below:

$$\tilde{\mathbf{m}}_{upd}(.) = \begin{cases} \tilde{m}_{upd}(O_1) = 0.13 \quad \tilde{m}_{upd}(O_2) = 0.44 \quad \tilde{m}_{upd}(O_3) = 0.22 \\ \tilde{m}_{upd}(H = O_1 \cup O_3) = 0.21 \end{cases} \tag{20.1}$$

- *Step 6.* Finally, the pignistic probabilities are calculated in order to take decisions about the object's nature: $P(H) = 0.56 \quad P(F) = 0.44$. Other pignistic probabilities of interest are: $P(O_1) = 0.235 \quad P(O_3) = 0.355$. It is obvious that the evidence supporting propositions *'target type is O_1'* and *'target type is O_3'* increase the support for proposition *'Hostile target'*. But the evidence for a target being *'Hostile target'* does not increase the support for the proposition *'target type is O_1'* or *'target type is O_3'*. These results illustrate and confirm the benefits we can expect from the application of the proposed approach.

For the completion of this study and to demonstrate its efficiency, two other possible radar measurements are considered: the possible presence of target type *'fighter'* (and related to it *'bomber'*) or the possible presence of target type *'airlift cargo'* (and related to it *'bomber'*):

$$\mathbf{m}_X^{'}(.) = \begin{cases} m_X(O_1) = 0.3 \\ m_X(O_2) = 0.2 \\ m_X(O_3) = 0.2 \\ m_X(O_1 \cup O_3) = 0.3 \\ m_X(\Theta) = 0 \end{cases} \quad \text{and} \quad \mathbf{m}_X^{''}(.) = \begin{cases} m_X(O_1) = 0.2 \\ m_X(O_2) = 0.3 \\ m_X(O_3) = 0.2 \\ m_X(O_1 \cup O_3) = 0.3 \\ m_X(\Theta) = 0 \end{cases}$$

The measurement $\mathbf{m}_{X'}(.)$ supports the probability for *'hostile fighter'*, additionally increasing the corresponding pignistic probability $P(H) = 0.65$ and decreasing the opposite one $P(F) = 0.35$. The measurement $\mathbf{m}_{X''}(.)$ supports *'friend's airlift cargo'*, additionally increasing the pignistic probability $P(F) = 0.41$ and decreasing $P(H) = 0.59$. It can be noted that both probabilities tend toward each other due to the lack of more categorical evidence supporting *'Hostile'*. The small difference remaining between them is due to the ambiguous evidence $O_2 \cap O_3$. The considered sub-case illustrates the single inefficient application of the proposed approach (but there is no reason to make categorical decisions if the available information does not provide any support for this).

In the alternative case of this example, when the target *'Friend'* is considered, the numerical results remain the same. They support the wrong decision, but have to be ignored because of the obvious conflict with the air-traffic control's schedule. This schedule excludes the appearance of a *'friend's fighter'* or a *'friend's bomber'*. Generalizing, there is no reason to check these propositions due to the lack of IFF-sensor's answer and because of the arising serious conflict with the air-traffic control rules. The case of arriving measurement $\mathbf{m}_X^{''}(.)$ is commented above as the single inefficient approach application.

The benefits of the proposed approach are also demonstrated in comparing the results with those obtained by the direct utilization of the mentioned database and TCN rule. For this purpose, the database consists of two separate databases (m_{DB}^H and m_{DB}^F) related with the propositions H and F respectively. Each database contains two columns (1,2 and 1,3 respectively). These granules can be used for the direct updating of $\mathbf{m}_X(.)$ so as to check both alternatives: $\mathbf{m}_{X'} \oplus \mathbf{m}_{DB}^H = \mathbf{m}_{upd}^H$ and $\mathbf{m}_{X''} \oplus \mathbf{m}_{DB}^F = \mathbf{m}_{upd}^F$. The pignistic probabilities obtained for both alternatives are:

$$P_{upd}^H(H) = 0.61,\ P_{upd}^H(F) = 0.39,\ P_{upd}^F(H) = 0.41,\ P_{upd}^F(F) = 0.59$$

The obtained probabilities thus show some improvement from the initial total ignorance, however this improvement does not suffice in practical application due to the high similarity of the results for the pignistic probabilities $P_{upd}^H(H)$ and $P_{upd}^F(F)$.

20.4 Conclusions

A new approach for a fast reduction of the uncertainty in the process of object identification has been proposed. The new class of fusion rules based on fuzzy T-conorm/T-norm operators is used for reducing ignorance according to the object's nature. This approach which combines fuzzy set theory and DSmT, utilizes the information from the adjoint sensor and additional information obtained from a priori defined objective and subjective considerations. This forms a database representing a set of fuzzy relations, correlating some measurement components expressed at different levels of abstraction. This approach generates its results from all available information about the stochastic events considered in the database and it improves the separation power of the decision process which is based on the generalized pignistic transformation.

20.5 References

[1] T. Bayes, *Essay toward solving a problem in the doctrine of changes*, Philosophical transactions on the royal society, London, 1763.

[2] S. Blackman, R. Popoli, *Design and Analysis of Modern Tracking Systems*, Artech House, 1986.

[3] Ph.L. Bogler, *Demspter-Shafer reasoning with applications to multisensor target identification systems*, IEEE Transactions on Systems, Man, and Cybernetics, SMC-17 (6), pp. 968–977, 1987.

[4] A. Dempster, *A generalization of Bayesian inference*, Journal of the Royal Statistical Society, Series B, Vol. 30, pp. 205–247, 1968.

[5] D. Hall, *Mathematical techniques in multisensor data fusion*, Artech house, 1992.

[6] J. Lowrance, T. Garvey, *Evidential reasoning: an implementation for multisensor integration*, Technical Note 307, Artificial Intelligence Center, International, Menlo Park, CA, 1983.

[7] J. Mendel, *Fuzzy Logic Systems for Engineering: A Tutorial*, in Proceedings of IEEE, pp. 345–377, 1995.

[8] J. Schubert, *Clustering belief functions based on attracting and conflictiing metalevel evidence*, Proceedings of IPMU conf., Annecy, France, 2002.

[9] G. Shafer, *A mathematical theory of evidence*, Princeton University Press, 1976.

[10] R.P. Singh, W.H. Bailey, *Fuzzy logic applications to multisensors-multitarget correlations*, IEEE Trans. on Aerospace and Electronic Systems, 33(3), 1997.

[11] F. Smarandache, J. Dezert (Editors), *Applications and Advances of DSmT for Information Fusion*, Vol. 1, American Research Press, Rehoboth, 2004. http://www.gallup.unm.edu/~smarandache/DSmT-book1.pdf.

[12] F. Smarandache and J. Dezert (Editors), *Applications and Advances of DSmT for Information Fusion*, Vol. 2, American Research Press, Rehoboth, 2006. http://www.gallup.unm.edu/~smarandache/DSmT-book2.pdf.

[13] A. Tchamova, J. Dezert, F. Smarandache, *A new class of fusion rules based on T-Conorm and T-Norm fuzzy operators*, Information and Security, An International Journal, Vol. 20, 2006.

[14] E. Waltz, J. Llinas, *Multisensor data fusion*, Artech House,1990.

[15] L.A. Zadeh, *Fuzzy sets*, Informat. Contr., Vol.8, pp. 338–353, 1965.

[16] L.A. Zadeh, *Outline of a new approach to the analysis of complex systems and decision processes*, IEEE Trans. on Systems, Man and Cybernetics, SMC-3.,1973.

[17] L.A. Zadeh, *Fuzzy sets and applications*, Selected papers, Wiley, 1987.