Tracking Applications with Fuzzy-Based Fusion Rules

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Abstract—**The objective of this paper is to present and evaluate the performance of a particular fusion rule based on fuzzy T-Conorm/T-Norm operators for two tracking applications: (1) Tracking Object's Type Changes, supporting the process of identification, (e.g. friendly aircraft against hostile ones, fighter against cargo) and consequently for improving the quality of generalized data association; (2) Alarms identification and prioritization in terms of degree of danger relating to a set of a priori defined, out of the ordinary dangerous directions. The aim is to present and demonstrate the ability of TCN rule to assure coherent and stable way for identification and to improve decision-making process in temporal way. A comparison with performance of DSmT based PCR5 fusion rule and Dempster's rule is also provided.**

Keywords—*Objects' type identification; Alarm classification; Data fusion; DSmT, TCN rule, PCR5 rule, Dempster's rule.*

I. INTRODUCTION

An important function of each surveillance system is to keep and improve targets tracks maintenance performance, as well as to provide a smart operational control, based on the intelligent analysis and interpretation of alarms coming from a variety of sensors installed in the observation area. Targets' type estimates can be used during different target tracking process stages for improving data to track association and for the quality evaluation of complicated situations characterized with closely spaced or/and crossing targets [1], [2]. It supports the process of identification, e.g. friendly aircraft against hostile ones, fighter against cargo. In such case, although the attribute of each target is invariant over time, at the attribute-tracking level the type of the target committed to the (unresolved) track varies with time and must be tracked properly in order to discriminate how many different targets are hidden in the same unresolved track. Alarms classification and prioritization [3],[4],[5],[6],[7],[8] is very challenging task, because in case of multiple suspicious signals (relating to a set of a priori defined, out of the ordinary dangerous directions), generated from a number of sensors in the observed area, it requires the most dangerous among them to be correctly recognized, in order to decide properly where the video camera should be oriented. There are cases, when some of the alarms generated could be incorrectly interpreted as false, increasing the chance to be ignored, in case when they are really significant and dangerous. That way the critical delay of the proper response could cause significant damages. In both cases above, the uncertainty and conflicts encountered in objects' and signals data, could weaken or even mistake the respective surveillance system decision. That is why a strategy for an intelligent, scan by scan, combination/updating of data generated is needed in order to provide the surveillance system with a meaningful output. In this paper we focus our attention on the ability of the so called T-Conorm-Norm (TCN) fusion rule, defined within Dezert-Smarandache Theory (DSmT) of plausible and paradoxical reasoning to improve the process of data fusion and to successfully finalize the decision-making procedures in both described surveillance cases. This work is based on preliminary research in [9],[10]. In section II we recall basics of Proportional Conflict Redistribution rule no.5 (PCR5), defined within DSmT. Basics of PCR5 based TCN fuzzy fusion rule are outlined in section III. Section IV presents the problem of alarms classification and examine the ability of TCN fusion rule to solve it. In section V the performance of TCN rule is analyzed related to the problem of target type tracking. In both sections, a comparative analysis of TCN rule solution with those, obtained by PCR5 and Dempster-Shafer's (DS) rule is provided. Concluding remarks are given in section VI.

II. BASICS OF PCR5 FUSION RULE

The general principle of Proportional Conflict Redistribution rules is to: *1)* calculate the conjunctive consensus between the sources of evidences; *2)* calculate the total or partial conflicting masses; *3)* redistribute the conflicting mass (total or partial) proportionally on non-empty sets involved in the model according to all integrity constraints. The idea behind the Proportional Conflict Redistribution rule no. 5 defined within DSmT [9] (Vol. 2) is to transfer conflicting masses (total or partial) proportionally to non-empty sets involved in the model according to all integrity constraints. Under Shafer's model assumption of the frame Θ, PCR5 combination rule for only two sources of information is defined as: $m_{PCR5}(\emptyset) = 0$ and $\forall X \in 2^{\Theta} \setminus \{\emptyset\}$

$$m_{PCR5}(X) = m_{12}(X) +$$
$$\sum_{\substack{X_2 \in 2^{\Theta} \setminus \{X\} \\ X_2 \cap X = \emptyset}} [\frac{m_1(X)^2 m_2(X_2)}{m_1(X) + m_2(X_2)} + \frac{m_2(X)^2 m_1(X_2)}{m_2(X) + m_1(X_2)}] \quad (1)$$

All sets involved in the formula (1) are in canonical form. $m_{12}(X)$ corresponds to the conjunctive consensus, i.e:

$$m_{12}(X) = \sum_{\substack{X_1, X_2 \in 2^{\Theta} \\ X_1 \cap X_2 = X}} m_1(X_1) m_2(X_2).$$

All denominators are different from zero. If a denominator is zero, that fraction is discarded. No matter how big or small is the conflicting mass, PCR5 mathematically does a better redistribution of the conflicting mass than Dempster-Shafer's rule since PCR5 goes backwards on the tracks of the conjunctive rule and redistributes the partial conflicting masses only to the sets involved in the conflict and proportionally to their masses put in the conflict, considering the conjunctive normal form of the partial conflict. PCR5 is quasi-associative and also preserves the neutral impact of the vacuous belief assignment.

III. BASICS OF TCN FUSION RULE

The T-Conorm-Norm rule of combination [11] represents a class of fusion rules based on specified fuzzy t-Conorm, t-Norm operators [16]. Triangular norms (t-norms) and Triangular conorms (t-conorms) are the most general families of binary functions that satisfy the requirements of the conjunction and disjunction operators, respectively. TCN rule is defined within DSmT based PCR5 fusion rule. Under Shafer's model assumption of the frame Θ, the TCN fusion rule for only two sources of information is defined as: $\tilde{m}_{TCN}(\emptyset) = 0$ and $\forall X \in 2^{\Theta} \setminus \{\emptyset\}$

$$\tilde{m}_{TCN}(X) = \tilde{m}_{12}(X)+$$
$$\sum_{\substack{X_2 \in 2^{\Theta} \setminus \{X\} \\ X_2 \cap X = \emptyset}} [\frac{m_1(X).Tnorm\{m_1(X), m_2(X_2)\}}{Tconorm\{m_1(X), m_2(X_2)\}}+$$
$$\frac{m_2(X).Tnorm\{m_2(X), m_1(X_2)\}}{Tconorm\{m_2(X), m_1(X_2)\}}] \quad (2)$$

where $\tilde{m}_{12}(X)$ corresponds to the conjunctive consensus, obtained by:

$$\tilde{m}_{12}(X) = \sum_{\substack{X_1, X_2 \in 2^{\Theta} \\ X_1 \cap X_2 = X}} Tnorm\{m_1(X_1), m_2(X_2)\}.$$

TCN fusion rule requires a normalization procedure :

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

The attractive features of TCN rule could be defined as: very easy to implement, satisfying the impact of neutral Vacuous Belief Assignment; commutative, convergent to idempotence, reflects majority opinion, assures adequate data processing in case of partial and total conflict between the information granules. The general drawback of this rule is related to the lack of associativity, which is not a main issue in temporal data fusion.

IV. ALARMS CLASSIFICATION APPROACH

The approach assumes all the localized sound sources to be subjects of attention and investigation for being indication of dangerous situations. The specific input sounds' attributes, emitted by each source, are sensor's level processed and evaluated in timely manner for their contribution towards correct alarms' classification (in term of degree of danger). The applied algorithm considers the following steps:

- Defining the frame of expected hypotheses as follows: $\Theta = \{\theta_1 = (E)mergency, \theta_2 = (A)larm, \theta_3 = (W)arning\}$. Here Shafer's model holds and we work on the power-set: $2^{\Theta} = \{\emptyset, E, A, W, E \cup A, E \cup W, A \cup W, E \cup A \cup W\}$. The hypothesis with a highest priority is *Emergency*, following by *Alarm* and then *Warning*.

- Defining an input rule base to map the sounds' attributes (so called *observations*) obtained from all localized sources into non-Bayesian basic belief assignments $m_{obs}(.)$.

- At the very first time moment $k = 0$ we start with a priori basic belief assignment (history) set to be a vacuous belief assignment $m_{hist}(E \cup A \cup W) = 1$, since there is no information about the first detected degree of danger according to sound sources.

- Combination of currently received measurement's bba $m_{obs}(.)$ (for each of located sound sources), based on the input interface mapping, with a history's bba, in order to obtain estimated bba relating to the current degree of danger $m(.) = [m_{hist} \oplus m_{obs}](.)$. TCN rule is applied in the process of temporal data fusion to update bba's associated with each sound emitter.

- Flag for an especially high degree of danger has to be taken, when during the a priori defined scanning period, the maximum Pignistic Probability [9] is associated with the hypothesis *Emergency*. In this work, we assume Shafer's model and we use the classical Pignistic Transformation [9], [15] to take a decision about the mode of danger. It is defined for $\forall A \in 2^{\Theta}$ by

$$BetP(A) = \sum_{X \in D^{\Theta}} \frac{|X \cap A|}{|X|} \cdot m(X) \quad (3)$$

where $|X|$ denotes the cardinality of X.

A. Simulation Scenario

A set of three sensors located at different distances from the microphone array are installed in an observed area for protection purposes, together with a video camera [13]. They are assembled with alarm devices: Sensor 1 with *Sonitron*, Sensor 2 with *E2S*, and Sensor 3 with *System Sensor*. In case of alarm events (smoke, flame, intrusion, etc.) they emit powerful sound signals with various duration and frequency of intermittence (Table 1), depending on the nature of the event.

Table 1 Sound signal parameters.

Continuous (*Warning*)	Intermittent-I (*Alarm*)	Intermittent-II (*Emergency*)
$f_{int} = 0$Hz	$f_{int} = 5$Hz	$f_{int} = 1$Hz
$T_{sig} = 10$s	$T_{sig} = 30$s	$T_{sig} = 60$s

The frequency of intermittencies f_{int}, associated with the localized sound sources is utilized in the specific input interface (the rule base) below.

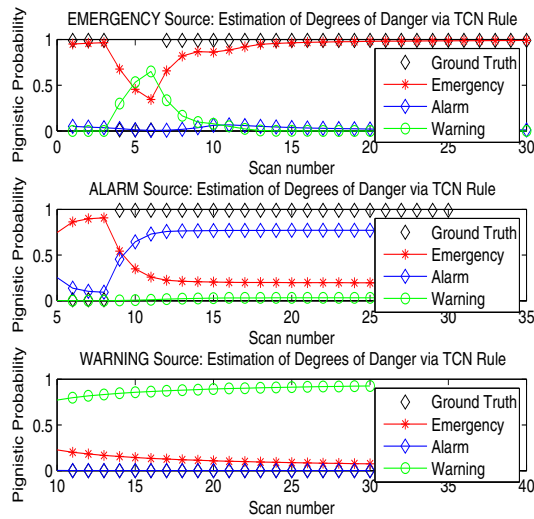**Rule 1**: if $f_{int} \rightarrow 1Hz$ then $m_{obs}(E) = 0.9$ and $m_{obs}(E \cup A) = 0.1$.

Fig. 1. TCN rule Performance for danger level estimation.

Rule 2: if $f_{int} \to 5Hz$ then $m_{obs}(A) = 0.7$, $m_{obs}(A \cup E) = 0.2$ and $m_{obs}(A \cup W) = 0.1$.

Rule 3: if $f_{int} \to 0Hz$ then $m_{obs}(W) = 0.6$ and $m_{obs}(W \cup A \cup E) = 0.4$.

Three main cases are estimated: the probabilities of modes, evaluated for Sensor 1 (associated with *Emergency* mode), Sensor 2 (associated with *Alarm* mode), and Sensor 3 (associated with *Warming* mode. The decisions should be governed at the video camera level, taken periodically, depending on: *1)* specificities of the video camera (time needed to steer the video camera toward a localized direction); *2)* time duration needed to analyze correctly and reliably the sequentially gathered information. We choose as a reasonable sampling period for camera decisions $T_{dec} = 20sec$, i.e. at every 10th scan.

B. TCN rule performance for danger level estimation.

Fig.1 shows the values of Pignistic Probabilities of each mode (*E*, *A*, *W*) associated with three sound emitters (1st source in *E* mode, (subplot on the top), 2nd source in *A* mode (subplot in the middle), and 3rd source in *W* mode, (subplot in the bottom)) during the all 30 scans. Each source has been perturbed with noises in accordance with the simulated *Ground Truth*, associated with particular sound source. These probabilities are obtained for each source independently as a result of sequential data fusion of $m_{obs}(.)$ sequence using TCN combinational rule. For a completeness of study and for comparison purposes, the respective performances of PCR5 and DS rule are presented in fig.2 and fig.3.

TCN rule shows a stable, quite proper and effective behavior, following the performance of PCR5 rule. A special feature of TCN rule performance are the smoothed estimates and more cautious decisions taken at the particular decisive scans.

The results obtained show the strong ability of PCR5 rule to take care in a coherent and stable way for the evolution of all possible degrees of danger, related to all the localized sources. It is especially significant in case of sound sources data
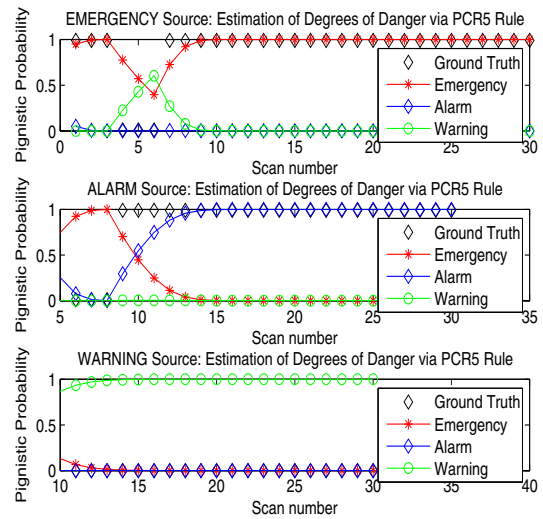

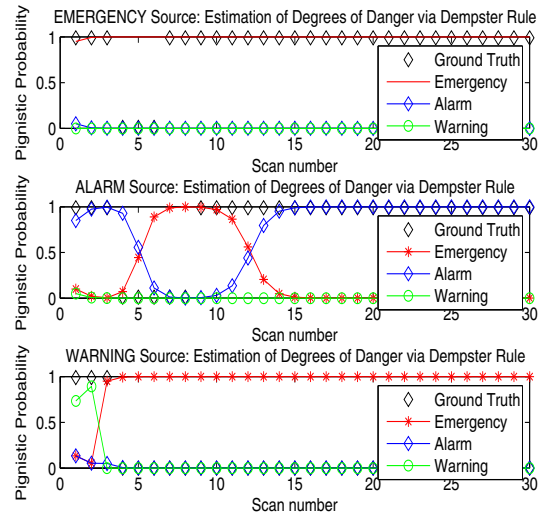Fig. 2. PCR5 rule Performance for danger level estimation.

Fig. 3. Dempster's rule Performance for danger level estimation.

discrepancies and conflicts, when the highest priority mode Emergency occurs. PCR5 rule prevents to produce a mistaken decision, that way prevents to avoid the most dangerous case without immediate attention. A similar adequate behavior of performance is established in cases of lower danger priority.

DS rule shows weakness in resolving the cases examined. In Emergency case, DS rule does not reflect at all new obtained informative observations supporting the Warning mode. This pathological behavior reflects the dictatorial power of DS rule realized by a given source [12], which is fundamental in Dempster-Shafer reasoning [14]. In our particular case however, DS rule leads to a right final decision by coincidence, but this decision could not be accepted as coherent and reliable, because it is not built on a consistent logical ground. In cases of lower dangers priority (perturbed Warning and Alarm mode), DS rule could cause a false alarm and can deflect the attention

from the existing real dangerous source by assigning a wrong steering direction to the surveillance camera.

V. TARGET TYPE TRACKING APPROACH

The problem can be simply stated as follows:

- Let $k = 1, 2, ..., k_{max}$ be the time index and consider M possible target types $T_i \in \Theta = \{\theta_1, \ldots, \theta_M\}$ in the environment; for example $\Theta = \{Fighter, Cargo\}$ and $T_1 \triangleq Fighter$, $T_2 \triangleq Cargo$; or $\Theta = \{Friend, Foe, Neutral\}$, etc.

- at each instant k, a target of true type $T(k) \in \Theta$ (not necessarily the same target) is observed by an attribute-sensor (we assume a perfect target detection probability here).

- the attribute measurement of the sensor (say noisy Radar Cross Section for example) is then processed through a classifier which provides a decision $T_d(k)$ on the type of the observed target at each instant k.

- The sensor is in general not totally reliable and is characterized by a $M \times M$ confusion matrix

$$\mathbf{C} = [c_{ij} = P(T_d = T_j | TrueTargetType = T_i)]$$

The goal is to estimate $T(k)$ from the sequence of declarations done by the unreliable classifier up to time k, i.e. how to build an estimator $\hat{T}(k) = f(T_d(1), T_d(2), \ldots, T_d(k))$ of $T(k)$. The principle of the estimator is based on the sequential combination of the current basic belief assignment (drawn from classifier decision, i.e. our *measurements*) with the prior bba estimated up to current time from all past classifier declarations.

The algorithm follows the next main steps:

- Initialization step (i.e. $k = 0$). Select the target type frame $\Theta = \{\theta_1, \ldots, \theta_M\}$ and set the prior bba $m^-(.)$ as vacuous belief assignment, i.e $m^-(\theta_1 \cup \ldots \cup \theta_M) = 1$ since one has no information about the first target type that will be observed.

- Generation of the current bba $m_{obs}(.)$ from the current classifier declaration $T_d(k)$ based on attribute measurement. At this step, one takes $m_{obs}(T_d(k)) = c_{T_d(k)T_d(k)}$ and all the unassigned mass $1 - m_{obs}(T_d(k))$ is then committed to total ignorance $\theta_1 \cup \ldots \cup \theta_M$.

- Combination of current bba $m_{obs}(.)$ with prior bba $m^-(.)$ to get the estimation of the current bba $m(.)$. Symbolically we will write the generic fusion operator as $\oplus$, so that $m(.) = [m_{obs} \oplus m^-](.) = [m^- \oplus m_{obs}](.)$. The combination $\oplus$ is done according either Demspter's rule (i.e. $m(.) = m_D(.)$) or PCR5 rule (i.e. $m(.) = m_{PCR5}(.)$).

- Estimation of True Target Type is obtained from $m(.)$ by taking the singleton of Θ, i.e. a Target Type, having the maximum of belief (or eventually the maximum Pignistic Probability).

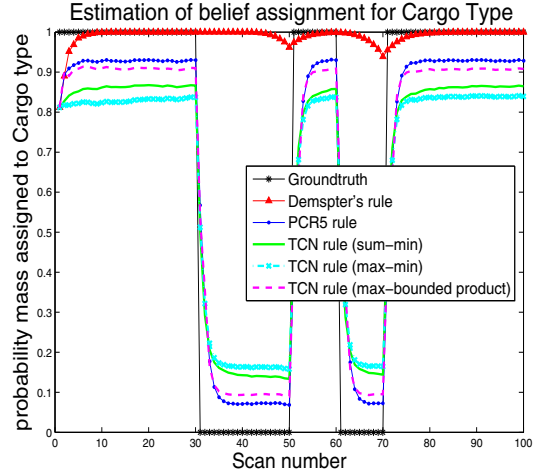- set $m^-(.) = m(.)$; do $k = k + 1$ and go back to step b).

Fig. 4.   Estimation of belief assignment for Cargo type.

A. Simulations results

In order to evaluate the performances of TCN-based estimator, a set of Monte-Carlo simulations on a very simple scenario for a 2D Target Type frame, i.e. $\Theta = \{(F)ighter, (C)argo\}$ is realized for classifier with a following confusion matrix:

$$\mathbf{C} = \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix}$$

We assume there are two closely spaced targets: Cargo and Fighter. Due to circumstances, attribute measurements received are predominately from one or another and both targets generates actually one single (unresolved kinematics) track. To simulate such scenario, a Ground Truth sequence over 100 scans was generated. The sequence starts with the observation of a Cargo type and then the observation of the target type switches two times onto Fighter type during different time duration. At each time step k the decision $T_d(k)$ is randomly generated according to the corresponding row of the confusion matrix of the classifier given the true target type (known in simulations). Then the algorithm from above is applied. The simulation consists of 10000 Monte-Carlo runs. The computed averaged performances (on the base of estimated belief masses obtained by the tracker) are shown on the figures 4 and 5. They are based on TCN fusion rule realized with different t-conorm and t-norm functions. On the same figures, for a comparison purposes, the respective performances of PCR5 and DS rule are presented. It is evident, that PCR5 fusion rule outperforms the results based on TCN rule, because PCR5 allows a very efficient Target Type Tracking, reducing drastically the latency delay for correct Target Type decision. TCN fusion rule shows a stable and adequate behavior, characterized with more smoothed process of re-estimating the belief masses in comparison to PCR5. TCN fusion rule with t-conorm=max and t-norm=bounded product reacts and adopts better than TCN with t-conorm=sum and t-norm=min, followed by TCN with t-conorm=max and t-norm=min.
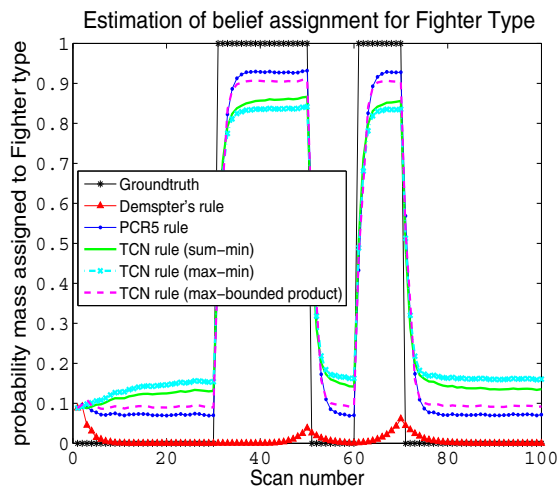
Fig. 5. Estimation of belief assignment for Fighter type.

presented: (1) Tracking Object's Type Changes, supporting the process of identification; (2) Alarms identification and prioritization in terms of degree of danger relating to a set of a priori defined, out of the ordinary dangerous directions. The ability of TCN rule to assure coherent and stable way of identification and to improve decision-making process in temporal way are demonstrated. Different types of t-conorm and t-norms, available in fuzzy set/logic theory provide us with richness of possible choices to be used applying TCN fusion rule. The attractive features of TCN rule is it's easy implementation and adequate data processing in case of conflicts between the information granules.

VII. ACKNOWLEDGMENT

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