Intelligent Alarm Classification Based on DSmT

Albena Tchamova
Jean Dezert

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***Abstract*—In this paper the critical issue of alarms' classification and prioritization (in terms of degree of danger) is considered and realized on the base of Proportional Conflict Redistribution rule no.5, defined in Dezert-Smarandache Theory of plausible and paradoxical reasoning. The results obtained show the strong ability of this rule to take care in a coherent and stable way for the evolution of all possible degrees of danger, relating to a set of a priori defined, out of the ordinary dangerous directions. A comparison with Dempster's rule performance is also provided. Dempster's rule shows weakness in resolving the cases examined. In Emergency case Dempster's rule does not respond to the level of conflicts between sound sources, leading that way to ungrounded decisions. In case of lowest danger's priority (perturbed Warning mode), Dempster's 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.**

***Keywords*—Alarm classification; DSmT; DST; data fusion.**

I. INTRODUCTION

The alarms classification and prioritization is a very challenging and difficult task. The encountered overflowing amount of alarms could become a serious source of confusion especially in dangerous cases, when one needs to take a proper immediate response. The problem is really critical, because the information available for performing alarms processing is uncertain, imprecise, even conflicting. 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.

A lot of work was done during the years, because the importance of this problem was recognized since the 1960s, in wide world cases of surveillance: in industry (powerplants, oil refineries), the clinical alarms in medicine, civilian and military monitoring. Nowadays surveillance (military and civilian) and environmental monitoring systems are characterized with a smart operational control, based on the intelligent analysis and interpretation of alarms coming from a variety of sensors installed in the observation area. Many approaches have been adopted and applied, addressing the problem in common. In [1] a generic neuro-expert system architecture for training neural networks in alarm processing is developed, which is satisfactory when the training set covers enough range of scenarios. An expert system with temporal reasoning for alarm processing is proposed in [2]. Fault detection and alarm processing in a loop system using a fault detection system is presented in [3]. In [4] the authors consider a methodology, based on both artificial neural networks and fuzzy logic for alarm identification. The tasks of alarm processing, fault diagnosis and comprehensive validation of protection performance are discussed and resolved in [5] using knowledge-based systems and model-based reasoning approach. In [6] alarm prioritization, using fuzzy logic is developed to prioritize the alarms during alarm floods which would ease the burden of operators with meaningless or false alarms. In case of multiple suspicious signals, generated from a number of sensors in the observed area, the problem of alarm classification requires the most dangerous among them to be correctly recognized, in order to decide properly where the video camera should be oriented. Because of uncertainty and conflicts encountered in signals' data, one needs to process, analyze and interpret correctly in timely manner all suspicious sound signals separately at particular sensor's levels in the observed area. Such kind of conflicts could weaken or even mistake the decision about the degree of danger in a critical situation. That is why a strategy for an intelligent, scan by scan, combination/updating of sounds data generated by each sensor is needed in order to provide the surveillance system with a meaningful output. There are various well known methods for combining information, which could be applied. The most used until now Dempster-Shafer Theory (DST) [9] proposes a suitable mathematical model for uncertainty representation, but its weak point in applications relates to the normalization factor, which yields to non-adequate results when sources to combine are highly conflicting. To overcome such drawback, we apply the Proportional Conflict Redistribution Rule no.5 (PCR5), defined in Dezert-Smarandache Theory (DSmT) of plausible and paradoxical reasoning [7]. It proposes a powerful and efficient way for combining and utilizing all the available information, allowing the possibility for conflicts and paradoxes between the elements of the frame of discernment. A comparison with DST performance based on Dempster's rule of combination[1] is also provided in order to evaluate the ability of DSmT to assure awareness about the alarms' classification and prioritization in case of sound source data discrepancies and to improve decision-making process about the degree of danger. In section II we recall basics of DST and

[1]This rule is also called Dempster-Shafer rule, and denoted DS for short.

Dempster's rule. Basics of PCR5 fusion rule are outlined in section III. Section IV relates to the decision making support used in order to decide which sound source is most dangerous. In section V, we present the problem of alarms classification and examine two solutions to solve it by using PCR5 and Dempster's rule. In section VI, the evaluation and comparative analysis of both solutions are provided on a given simulation scenario, that includes three sensors, generating three types of signals (warning, alarm and emergency). Concluding remarks are given in section VII.

II. Basics of DST

DST [9] proposes a suitable mathematical model for uncertainty representationLet $\Theta = \{\theta_1, \theta_2, \ldots, \theta_n\}$ be a frame of discernment of a problem under consideration containing n distinct elements θ_i, $i = 1, \ldots, n$. A basic belief assignment (bba, also called a belief mass function) $m(.) : 2^\Theta \rightarrow [0,1]$ is a mapping from the power set of Θ (i.e. the set of subsets of Θ), denoted 2^Θ, to $[0,1]$, that must satisfy the following conditions: 1) $m(\emptyset) = 0$, i.e. the mass of empty set (impossible event) is zero; 2) $\sum_{X \in 2^\Theta} m(X) = 1$, i.e. the mass of belief is normalized to one. $m(X)$ represents the mass of belief exactly committed to X. The vacuous bba characterizing full ignorance is defined by $m_v(.) : 2^\Theta \rightarrow [0;1]$ such that $m_v(X) = 0$ if $X \neq \Theta$, and $m_v(\Theta) = 1$. From any bba $m(.)$, the belief function $Bel(.)$ and the plausibility function $Pl(.)$ are defined as $\forall X \in 2^\Theta$: $Bel(X) = \sum_{Y | Y \subseteq X} m(Y)$ and $Pl(X) = \sum_{Y | X \cap Y \neq \emptyset} m(Y)$. $Bel(X)$ and $Pl(X)$ are classically seen as lower and upper bounds of an unknown probability $P(X)$ of X. Dempster-Shafer (DS) rule of combination [9] is a mathematical operation, denoted $\oplus$, which corresponds to the normalized conjunctive fusion rule. Based on Shafer's model of the frame, the combination of two independent and distinct sources of evidences characterized by their bba $m_1(.)$ and $m_2(.)$ and related to the same frame of discernment Θ is defined by $m_{DS}(\emptyset) = 0$, and $\forall X \in 2^\Theta \setminus \{\emptyset\}$ by

$$m_{DS}(X) = [m_1 \oplus m_2](X) = \frac{m_{12}(X)}{1 - K_{12}} \tag{1}$$

where

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

corresponds to the conjunctive consensus on X between the two sources of evidence. K_{12} is the total *degree of conflict* between the two sources of evidence defined by

$$K_{12} \triangleq m_{12}(\emptyset) = \sum_{\substack{X_1, X_2 \in 2^\Theta \\ X_1 \cap X_2 = \emptyset}} m_1(X_1) m_2(X_2) \tag{3}$$

DS rule is commutative and associative. The weak point of this rule is its behavior when $K_{12} \rightarrow 1$ because it can generate unexpected (at least very disputable) results [11]. When $K_{12} = m_{12}(\emptyset) = 1$, the two sources are said to be in total conflict and their combination cannot be applied since DS rule is mathematically not defined because of $0/0$ indeterminacy [9].

III. Basics of PCR5 fusion rule

The idea behind the Proportional Conflict Redistribution rule no. 5 (see [7], Vol. 3) is to transfer conflicting masses (total or partial) proportionally to non-empty sets involved in the model according to all integrity constraints. The general principle of PCR rules is then 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. Under Shafer's model assumption of the frame Θ, the PCR5 combination rule for only two sources of information is defined as: $m_{PCR5}(\emptyset) = 0$ and $\forall X \in 2^\Theta \setminus \{\emptyset\}$

$$m_{PCR5}(X) = m_{12}(X) + \sum_{\substack{Y \in 2^\Theta \setminus \{X\} \\ X \cap Y = \emptyset}} [\frac{m_1(X)^2 m_2(Y)}{m_1(X) + m_2(Y)} + \frac{m_2(X)^2 m_1(Y)}{m_2(X) + m_1(Y)}] \tag{4}$$

where $m_{12}(X)$ corresponds to the conjunctive consensus on X between the two sources and where all denominators are different from zero. All sets involved in the formula are in canonical form. All denominators are different from zero. If a denominator is zero, that fraction is discarded. No matter how big or small the conflicting mass is, PCR5 mathematically does a better redistribution of the conflicting mass than DS 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 preserves the neutral impact of the vacuous belief assignment.

IV. Decision-making support

In this work, we assume Shafer's model and we use the classical Pignistic Transformation [7], [10] to take a decision about the mode of danger. The pignistic probability (Pign.Proba), also called the betting probability (BetP) is defined for $\forall A \in 2^\Theta$ by

$$BetP(A) = \sum_{X \in D^\Theta} \frac{|X \cap A|}{|X|} \cdot m(X) \tag{5}$$

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

V. Alarms Classification Approach

Our approach for alarms classification assumes all the localized sound sources to be subjects of attention and investigation for being indication of dangerous situations. The specific attributes of input sounds, 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 input sounds attributes generated by each sensor, at each time moment (scan) concern the frequency of intermittence, f_{int} and sound signal duration, T_{sig}. A particular relationship between the specific values of f_{int} and associated corresponding degree of danger is established, i.e to map input specific sensor level data into the frame of discernments, concerning the level of abstraction *Degree of Danger*= {*Emergency*, *Alarm*, *Warning*}. Then the process consists in temporal sensors' level sound signals' attribute updating on the base of PCR5 fusion rule. Our motivation for attribute fusion is inspired from the necessity to ascertain the degree of danger, associated with all localized sound sources separately, in order to quickly focus on the most dangerous alarm information and to take immediate and correct feedback actions to decide properly where the video camera should be oriented. The applied algorithm considers the following steps:

• We define the frame of expected hypotheses according to the respective degree of danger associated with the attributes's specific values as follows: $\Theta = \{\theta_1 = (E)mergency, \theta_2 = (A)larm, \theta_3 = (W)arning\}$. The hypothesis with a highest priority is *Emergency*, following by *Alarm* and then *Warning*. These hypotheses are exclusive and exhaustive, hence Shafer's model holds and we work on power-set: $2^{\Theta} = \{\emptyset, E, A, W, E \cup A, E \cup W, A \cup W, E \cup A \cup W\}$.

• A rule-base is defined in order to establish the relationships between the sounds' attributes associated with all localized sources and corresponding degrees of danger, in the form:

Rule 1: if *attributes-type 1* then *Emergency*
Rule 2: if *attributes-type 2* then *Alarm*
Rule 3: if *attributes-type 3* then *Warning*

where attributes types 1, 2 and 3 could be specific sounds' attributes values, which are informative enough to be processed and evaluated for their contribution towards correct alarms' classification. In this rule base *attributes-type 1* is a sound's attribute, which is typical for degree of danger *Emergency*, *attributes-type 2* is typical for *Alarm*, *attributes-type 3* for *Warning*. In our case the frequency of intermittencies (if the signal is intermittent) f_{int}, associated with the localized sound sources is utilized. Then the following specific rule-base is used as an input interface to map the sounds' attributes (so called *observations*) obtained from all localized sources into non-Bayesian basic belief assignments $m_{obs}(.)$:

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

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 $m_{obs}(W \cup A \cup E) = 0.4$.

If the value of the sound attribute received is close to the particular sound signal parameter for Emergency, our bba is constructed in way that it will consider the hypothesis *Emergency* and also the reasonable in this case composite proposition ($E \cup A$), representing a possible partial uncertainty. If the value obtained is close to the particular sound signal parameter for *Alarm*, our bba is constructed in way that it will consider the hypothesis *Alarm* itself and also the reasonable in that case composite propositions $A \cup E$ and $A \cup W$. Assigning a higher mass of belief to $A \cup E$ than to $A \cup W$ is to take care about the possibility for *Emergency* case. If the value obtained is close to the particular sound signal parameter for *Warning*, our bba is constructed in way that it will consider the hypothesis *Warning* and also the composite proposition $E \cup A \cup W$, representing the case of full ignorance, in order to take care about possibility for *Alarm* and especially for *Emergency* case. All the belief masses not already assigned to singletons (E, A or W) are assigned to the reasonable partial uncertainties reflecting the possible noise perturbations in the observed information.

• 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 $m(.) = [m_{hist} \oplus m_{obs}](.)$. PCR5 and DS are tested 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 [7] is associated with the hypothesis *Emergency*.

For security purpose, it is very important to keep updating sequentially the estimation one has on the state of the true modes of sound emitters, even if they are in the lowest priority mode (i.e. in warning mode only) in order to prevent unexpected alarm's changes.

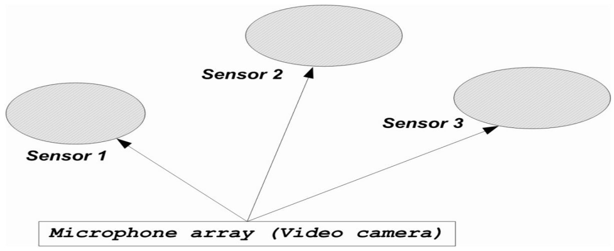

Fig. 1. Scenario.

VI. Simulation Scenario and Results

In our simulation scenario (Fig. 1) 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 [8]. It is assumed, that sensors are assembled with alarm devices, as follows: Sensor 1 with *Sonitron*, Sensor 2 with *E2S*, and Sensor 3 with *System Sensor* companies alarm devices. In case of alarm events (smoke, flame, intrusion, etc.) the alarm devices emit powerful sound signals with various duration and frequency of intermittence depending on the nature of the event. dangerous signal source. These sensors are used for the purpose of estimation the level of danger/threat for each place where they are located. Data, obtained from each source are processed and analyzed at particular sensor's level independently, in consecutive time

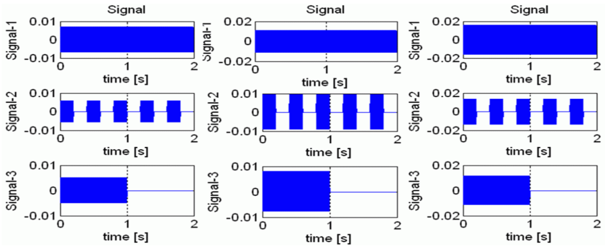

Fig. 2. *Sonitron, E2S, System Sensor* Sound Characteristics.

moments, with regard to all possible degrees of danger: $\theta_1 = (E)mergency$, $\theta_2 = (A)larm$, and $\theta_3 = (W)arning$. Doing this one could find the first suspicious moment, when

Table 1 Sound signal parameters.

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

the situation could become eventually dangerous.

The sound signals representing *Warning*, *Alarm* and *Emergency*, emitted from alarm devices, produced by Sonitron, E2S and System Sensor companies used in our simulation (Table 1) are shown on Fig. 2. The first (left) column of Fig. 2 relates to Sonitron, the second column to E2S, and the third (right) column relates to System Sensor devices. The first row of this figure represents the signal 1 for *Warning*, second row represents signal 2, for *Alarm*, and the last third row represents signal 3, for *Emergency* case. The *Alarm* signal is intermittent with a frequency of intermittence $f_{int} = 5Hz$ and a duration $T_{sig} = 30s$, so called type I. The *Emergency* sound signal is intermittent with a frequency of intermittence $f_{int} = 1Hz$ and duration $T_{sig} = 60s$, so called type II. The *Warning* signal is continuous with $f_{int} = 0Hz$ and $T_{sig} = 10s$.

Our simulation scenario considers a true degree of danger associated with the sound sources as follows: Emergency mode for the first sound emitter, Alarm mode for the second, and Warning mode - for the third one. The three sources are processed in parallel and because of possible sound perturbations we assume that possible random changes can be observed over the scans for a given mode. We therefore introduce some switches between the three modes *Emergency*, *Alarm* and *Warning* to simulate what can happen in practice (what we call *ground truth* and displayed with black plots on our next figures 3 and 4. According to this, three main cases are estimated:

- The most interesting for us it is the estimation of danger level by sensor 1, associated with *Emergency* mode. In our simulation, the *The Ground Truth* associated with Sensor 1 considers that during scans 1–3 the observations generated support the *Emergency* mode (the highest level of danger). From scan 4 to scan 6 the observations generated support the *Warning* mode (the lowest level of danger). From scan 7 to scan 30 the observations generated support again *Emergency* mode. Such kind of scenario is important in the real world cases because sources data can be deteriorated by noise perturbations and therefore some possible conflicts arise between observations from scan to scan. We assume that a conflict occurs in sounds data between *Emergency* and *Warning* modes, because it could weaken strongly the decision taken. It could become a reason to ignore the significance of out of ordinary, dangerous situation.
- The second interesting case concerns the estimation of probabilities of modes, associated with the sound emitter 2 working in *Alarm* mode. The *Ground Truth* has been a little bit changed with respect to the ground truth simulated for sensor 1. We assume that during scans 1–3 the observations generated support correctly the *Alarm* mode. From scan 4 to scan 8 the observations generated support the *Emergency* mode because of noise perturbations. From scan 9 to scan 30 the observations generated support again correctly the *Alarm* mode.
- The third interesting case concerns the estimation of the probability of modes, associated with the third emitter working in *Warning* mode. In our simulation of this case, we considers that during scans 1–2 the observations generated support correctly the *Warning* mode. From scan 3 to scan 5 the observations generated support the *Emergency* mode because of some possible noise perturbations. From scan 6 to scan 30 the observations generated support again correctly the *Warning* mode.

As a result of processing and analyzing sounds' data, obtained from the three sources, processed in parallel, one establishes at each scan, for each source the Pignistic probabilities, associated with all the considered modes of danger. 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, we should establish the decision about the most probable mode of danger, associated with each sound source, that way to declare directions for steering the video camera. For our scenario, the decisive scans will be 10th, 20th, and 30th. In the next two subsections we analyze the performances of PCR5 and DS to conclude on their ability (or inability) to correctly identify the alarm modes for the prioritization purpose.

A. PCR5 rule performance for danger level estimation.

Figure 3 shows the values of Pignistic Probabilities of each mode (*Emergency*, *Alarm*, *Warning*) associated with three sound emitters (1st source in *Emergency* mode, (subplot on the top), 2nd source in *Alarm* mode (subplot in the middle), and 3rd source in *Warning* mode, (subplot in the bottom)) during the all 30 scans. Each source has been perturbed with noises in

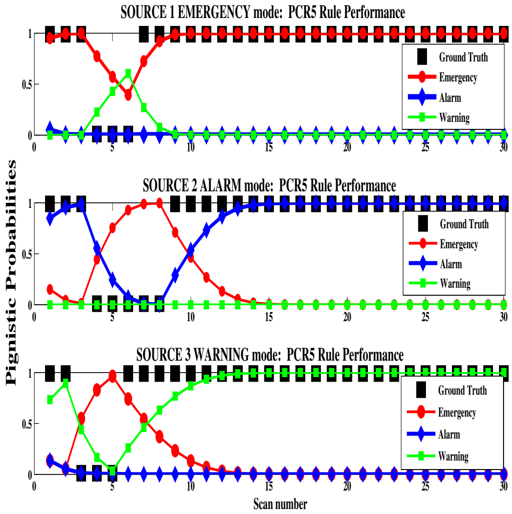

Fig. 3. PCR5 rule Performance for danger level estimation.

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 PCR5 combinational rule. For each source, we analyze the probabilities of its modes obtained with BetP computed from PCR5 rule and the corresponding decisions for steering the camera at scans no. 10, 20, and 30.

Decision taken by PCR5 rule at scan 10*:*

For source 1, associated with *Emergency* mode (Fig. 3, top-subplot), Pign.Proba established by PCR5 at scan 10 are as follows: $BetP(E) = 1.0$, $BetP(A) = 0$, and $BetP(W) = 0$. During the first scans one has $BetP(E) < 1$ because of the impact of the full uncertainty at the beginning. During the transition period between scans 4 and 6 the Pignistic Probability $BetP(E)$ decreases near to 0.4, and in a meantime $BetP(W)$ increases near to 0.6, reflecting that way the new observations supporting the *Warning* mode. After reestablishing the proper sound signal at scan 7, the PCR5 combination rule leads to quick re-estimation of belief masses, assigned to the right *Emergency* mode. One sees clearly the efficiency of PCR5 to detect a mode switch from the sequential fusion of $m_{obs}(.)$. At this processing stage, after decisive 10th scan, PCR5 rule takes a correct, reliable decision that $BetP(E) = 1.0$, assuring that camera will steer at this direction with highest priority.

For source 2, associated with *Alarm* mode, (Fig. 3, middle-subplot), Pign.Proba established by PCR5 are as follows: $BetP(E) = 0.5$, $BetP(A) = 0.5$, and $BetP(W) = 0$. At first scans, $BetP(A) < 1$, because of the full uncertainty at the very first time moment, and then $BetP(A) \to 1$. During the transition time between scans 4 and 8, $BetP(A)$ gradually decreases, while $BetP(E)$ gradually increases. During this period PCR5 rule takes attention according to the mode with the highest priority, i.e. the *Emergency* mode. Starting from scan 9 PCR5 rule reestablishes gradually (and enough quickly after a short delay) the probability mass assigned to *Alarm* mode. At the end of scan 10 PCR5 rule keeps $BetP(A) \approx BetP(E)$, staying cautious about *Emergency*, but this rule is on the way of fully reestablishing the beliefs in the proper *Alarm* mode for this case and to forget the mistaken *Emergency* mode.

For source 3, associated with *Warning* mode, (Fig. 3, subplot in the bottom), Pign.Proba established by PCR5 are as follows: $BetP(E) = 0.2$, $BetP(A) = 0$, and $BetP(W) = 0.8$. Until scan 10, because of the sound attributes measurement conflicts, the PCR5 rule gives some support (non null probability) to *Emergency* mode and also to *Warning* mode. Until scan 10, its behavior is cautious about *Emergency* mode, and during this time period it doesn't establish a hard decision. PCR5 results makes sense, because the decision about *Warning* mode is not decisive/firm.

Decision taken by PCR5 rule at scan 20 *and scan* 30*:*

From scan 15 on, and for all sound sources 1,2 and 3, PCR5 rule estimation is fully adequate and reasonable.

For source 1, associated with *Emergency* mode, one has: $BetP(E) = 1$, $BetP(A) = 0$, and $BetP(W) = 0$.

For source 2, associated with *Alarm* mode: $BetP(E) = 0$, $BetP(A) = 1$, and $BetP(W) = 0$.

For source 3, associated with *Warning* mode: $BetP(E) = 0$, $BetP(A) = 0$, and $BetP(W) = 1$.

These Pign.Proba remain firmly one and the same at scans 20 and 30, associating in stable way the highest priority danger to sound source 1 as expected in such scenario.

B. Dempster's rule performance for danger level estimation.

The corresponding figure 4 shows the values of Pignistic Probabilities of each mode (*Emergency*, *Alarm*, *Warning*) associated with three sound emitters (1st source in *Emergency* mode, (top subplot), 2nd in *Alarm* mode (middle subplot), and 3rd in *Warning* mode (bottom subplot)) during all 30 scans, which are obtained as a result of sequential data fusion of $m_{obs}(.)$ sequence using DS of combination.

Decision taken by Dempster's rule at scan 10*:*

For source 1, associated with *Emergency* mode (Fig. 4, subplot on the top), Pign.Proba established by DS are as follows: $BetP(E) = 1$, $BetP(A) = 0$, and $BetP(W) = 0$. It is obvious, that during the scans 1 and 10 DS is unable to respond to the new observations, arriving in scan 4 and supporting the *Warning* mode. DS does not reflect at all the new available data, which are informative and should be taken into account. This pathological behavior could lead to wrong decisions. In our particular case however, DS leads to a right final decision at scan 10 by coincidence, but this decision could not be accepted as coherent and reliable, because it is not built on a consistent logical ground. Taking important decisions by chance could be critically wrong and could cause valuable damages.

For source 2, associated with *Alarm* mode (Fig. 4, middle subplot), Pign.Proba established by DS are as follows: $BetP(E) = 1$, $BetP(A) = 0$, $BetP(W) = 0$. During the scans 1 and 10, because of the conflicts in obtained measurements, DS generates a totally wrong Pign.Proba $BetP(E) = 1.0$ assigned to *Emergency*, producing a hard decision for *Emergency* case. DS leads here to false alarm. That way video camera will be steered in wrong direction, which in reality is not the direction with highest priority. It means, that the true most dangerous direction for reaction will be ignored.

For source 3, associated with *Warning* mode (Fig. 4, subplot in the bottom), Pign.Proba established by DS are as follows: $BetP(E) = 1$, $BetP(A) = 0$ and $BetP(W) = 0$. Here the same false alarm situation is established as in source 2. Actually at scan 10 DS establishes totally wrong decisions for source 2 and source 3. The only right decision taken for source 1 is obtained by coincidence (because of not responding behaviour of the rule) and has no logical ground.

Decision taken by Dempster's rule at scan 20*:*

At scan 20, according to source 1, DS keeps its nonresponding behaviour, leading to right, but taken by coincidence decision. According to sensor 3 DS keeps the false alarm, as at scan 10. It succeeds to take a right decision for source 2, associated with *Alarm* mode, after a longer delay in reestablishing the belief masses for *Alarm*, in comparison with PCR5 rule.

Decision taken by Dempster's rule at scan 30*:*

At this scan DS succeeds to keep the right decision for source 2. However, it keeps performing as at scan 20, producing right, but logically ungrounded decision for source 1, and false alarm for source 3. Taking important decisions, concerning security, by chance, could be critically wrong and dangerous. Steering camera toward wrong direction, on the base of false alarm, could become critical too, because that way the proper camera response will be mistaken.

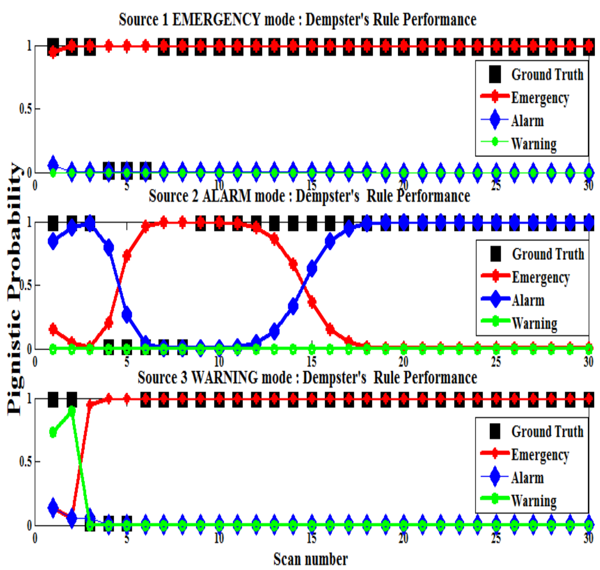

Fig. 4. Dempster's rule Performance for danger level estimation.

VII. Conclusions

In this paper the alarms' identification and prioritization (in terms of degree of danger) has been considered and realized using PCR5 rule of combination in order to estimate the proper degree of danger, especially in crowded scene, where events could happen at a set of a priori defined dangerous directions. The method utilized is based on the sequential fusion of the sound sources information obtained by two-dimensional microphone array defining the positions of the sources in surveillance area converted into basic belief assignments. A comparison of performance of PCR5 rule with respect to the performance of Dempster's rule has been done. 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 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. Dempster's rule shows weakness in resolving the cases examined. In *Emergency* case, Dempster's rule does not respond to the level of conflicts between sound sources, leading that way to ungrounded decisions. In cases of lower danger's priority (perturbed Warning and Alarm mode), Dempster's 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. In real world cases involving a broad surveillance area and multiple located sound sources, it becomes very important to realize distributed parallel processing with respect to the number of sources, in order to have correct decision in the proper time.

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