

Selection of sources as a prerequisite for information fusion with application to SLAM*

Xinde Li¹, Jean Dezert², Xinhan Huang¹

¹ Intelligent Control and Robotics Laboratory, Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China. (xdl825@163.com)

² ONERA, 29 Av. de la Division Leclerc, 92320 Châtillon, France. (jean.dezert@onera.fr)

Abstract - *We consider in this work evidential sources of information and propose a very general Evidence Supporting Measure of Similarity (ESMS) for selecting the most coherent subset of sources to combine among all sources available at each instant. The methodology proposed here coupled with a DSMT-based fusion machine is tested in robotics for the automatic estimation of an unknown simulated environment with obstacles where an autonomous mobile Pioneer II robot with sonar sensors evolves. Our simulation results are based on the fusion of similar and equireliable sensors but same approach can also be used with dissimilar sources as well by using a discounting method taking into account the reliability of each sensor. Our results show clearly the benefit of the selection of the sources as prerequisite for improvement of information fusion.*

Keywords: Source selection, Information fusion, Evidence supporting measure of similarity (ESMS), DSMT, Self Localization And Mapping (SLAM).

1 Introduction

The information fusion technology originated from the end of seventies results from the development of information science. Especially, since ten years or so ago, with the transfer of information fusion technology from the military applications to civil ones, whether the control architectures or the fusing arithmetic have been developed very rapidly [7] for dealing with imperfect information (incomplete, imprecise, uncertain, inconsistent). Many theoretical frameworks aside the classical probability theory have been developed to capture the different aspects of uncertainty (randomness, fuzzyness, non-specificity, etc) for artificial reasoning. Among all theories, the Mathematical Theory of Evidence or DST [10] and the recent DSMT (Dezert-Smarandache Theory) [11] offer interesting issues to combine uncertain sources of information expressed in term of belief functions. In these frameworks many fusion rules have been proposed by different authors, the most common ones being Dempster's rule [10], Yager's

rule [16], Dubois and Prade's rule [3] and the most recent ones based on proportionalization like minC [1] and PCR1-PCR5 rules [13, 14]. The main idea of this paper is the development of pre-processing task of the fusion in order to select the "best" subset of sources of information to combine with respect to a pre-defined criteria also called measure of similarity (or consistency) between sources. By a proper choice of consistent sources, we can decrease the conflict before applying the fusion rule (whatever the rule we choose), and thus will improve the correctness and precision of the fusion result as it will be shown in the sequel. In Section 2, we present shortly the general principle of the fusion machine and more specifically the DSMT-based fusion machine. In Section 3, we present the method for selecting consistent sources based on a general similarity function. Simulations results obtained by the DSMT-based fusion machine coupled with the sources selection method for Self Localization And Mapping (SLAM) of a Pioneer II autonomous robot will be presented and discussed in section 4.

2 The Fusion Machine

2.1 General principle

The general principle of a fusion machine consists in k sources of evidences (i.e. the inputs) providing basic belief assignments over a propositional space generated by elements of a frame of discernment Θ and set operators endowed with eventually a given set of integrity constraints which depend on the nature of elements of the frame. The set of belief assignments must then be combined with a fusion operator. Since in general the combination of uncertain information yields a degree of conflict, say K , between sources, this conflict must be managed by the fusion operator/machine. The way the conflict is managed is the key of the fusion step and makes the difference between the fusion machines. The fusion can be performed globally/optimally (when combining the sources in one derivation step all together) or sequentially (one source after another as in Fig. 1). The sequential fusion processing (well adapted for temporal fusion) is natural and more simple than the global fusion but in general remains only suboptimal if the fusion rule chosen is not associative, which

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is the case for most of fusion rules, but Dempster's rule. In this paper, the sequential fusion based on the PCR5 rule [13, 14] has been chosen because PCR5 has shown good performances in works where it has already been tested [5, 6] and because the sequential fusion is much more simple to implement and to test. The PCR5 fusion rule formula for k sources is possible and has also been proposed [13] but is much more difficult to implement and has not been tested yet. A more intuitive PCR rule (denoted PCR6) for the fusion of $s > 2$ sources proposed very recently by Martin and Osswald in [6], which outperforms PCR5, could be advantageously used in the fusion machine instead PCR5. Such an idea is currently under investigation and new results will be reported in a forthcoming publication. We present in more details in next section the DSMT-based fusion machine.

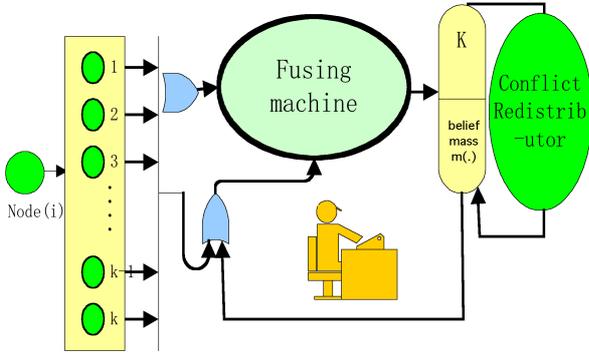


Fig. 1: General sequential fusion machine

2.2 DSMT-based Fusion machine

In this section we present the DSMT-based fusion machine adopted here for our SLAM application; more precisely for map reconstruction of the unknown environment where a mobile robot evolves. This choice was motivated by preliminary studies [5] which have shown the usefulness of DSMT [11, 2] for the SLAM problem in robotics with respect to a more conventional approach based on DST. The main advantage of DSMT is to deal with any models of representation (free-DSM model, hybrid DSM and/or Shafer's model for the frame of the fusion problem). DSMT is a new, general and flexible arithmetic of fusion, which can solve the fusion problem of different tiers including data-tier, feature-tier and decision-tier, and can be used to solve static or dynamic¹ fusion problems. DSMT main advantage lies in its ability to combine imprecise, uncertain and highly conflicting information. We just remind briefly the basis of DSMT and shortly introduce the last appealing fusion rule (rule no 5) based on Proportional Conflict Redistribution (PCR5) proposed recently in [13, 14]. We will show in section 4 how the PCR5-based fusion machine coupled with the ESMS filter will perform successfully the SLAM.

¹i.e. when model and/or frame changes with time.

2.2.1 Basis of DSMT

1. We denote $\Theta = \{\theta_1, \dots, \theta_n\}$ the frame of the problem. The basic idea of DSMT is to consider all elements of Θ as not precisely defined and separated, so that no refinement of Θ into a new finer set Θ^{ref} of disjoint hypotheses is possible in general (at least in most of fusion problems involving vague elements expressed in natural language whose intrinsic nature is continuous), unless some integrity constraints are truly known and in such case they will be included in the DSMT model of the frame. Shafer's model [10] assumes all $\theta_i, i = 1, \dots, n$ to be truly exclusive and appears only as a special case of DSMT hybrid model in DSMT.
2. The *hyper-power set* D^Θ [11] is defined as the set of all propositions built from elements of the frame Θ with \cap and \cup operators such that:

- (a) $\emptyset, \theta_1, \dots, \theta_n \in D^\Theta$.
- (b) If $A, B \in D^\Theta$, then $A \cap B$ and $A \cup B$ belong to D^Θ .
- (c) No other elements belong to D^Θ , except those obtained by using rules 1 or 2.

When Shafer's model holds, D^Θ reduces to the classical power set 2^Θ . Without loss of generality, we denote G^Θ the general set on which will be defined the basic belief assignments (or masses), i.e. $G^\Theta = 2^\Theta$ when DST is adopted or $G^\Theta = D^\Theta$ when DSMT is preferred instead, like in this work.

3. From a frame Θ , we define a general basic belief assignment (gbba) as a mapping $m(\cdot) : G^\Theta \rightarrow [0, 1]$ associated to a given source, say s , of evidence as

$$m_s(\emptyset) = 0 \quad \text{and} \quad \sum_{A \in G^\Theta} m_s(A) = 1 \quad (1)$$

$m_s(A)$ is the gbba of A committed by the source s . The belief and plausibility of A are defined² as:

$$\text{Bel}(A) \triangleq \sum_{\substack{B \subset A \\ B \in G^\Theta}} m(B) \quad \text{and} \quad \text{Pl}(A) \triangleq \sum_{\substack{B \cap A \neq \emptyset \\ B \in G^\Theta}} m(B) \quad (2)$$

4. When the free DSM model holds³, the conjunctive consensus, called DSM classic rule (DSMC) of two gbba $m_1(\cdot)$ and $m_2(\cdot)$ is given $\forall C \in D^\Theta$ by [11]:

$$m_{DSMC}(C) = \sum_{\substack{A, B \in D^\Theta \\ A \cap B = C}} m_1(A)m_2(B) \quad (3)$$

D^Θ being closed under \cup and \cap operators, DSMC guarantees that $m_{DSMC}(\cdot)$ is a proper gbba. DSMC is commutative and associative and can be used for the fusion of sources involving fuzzy concepts whenever the free-DSM model fits with the problem. It can be easily extended for the fusion of $k > 2$ independent sources as well - see also [11].

²The index of the source has been omitted for simplicity.

³i.e. all elements of Θ can be considered as partially overlapping because of their fuzzy intrinsic nature.

2.2.2 The PCR5 fusion rule

When integrity constraints are introduced in the model, one has to deal with the conflicting masses, i.e. all the masses that would become assigned to the empty set through DSmC rule. Many fusion rules (mostly based on Shafer's model) have been proposed [9] for managing the conflict. Among these rules, the Dempster's rule [10] redistributes the *total conflicting mass* over all propositions of 2^Θ through a simple normalization step. This rule has been the source of debates and criticisms because of its unexpected/counter-intuitive behavior in some cases. Many alternatives have then been proposed [9, 11] for overcoming this drawback. In DSmT, we have first extended the Dubois & Prade's rule [3, 11] for taking into account any integrity constraints in the model and also the possible dynamicity of the model and the frame. This first general fusion rule, called DSmH (DSm Hybrid) rule, consists just in transferring the partial conflicts onto the partial ignorances⁴. DSmH rule has been recently and advantageously replaced by the more sophisticated Proportional Conflict Redistribution rule no. 5 (PCR5) [14]. In our opinion, PCR5 does a better redistribution of the conflicting mass than Dempster'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 preserves the neutral impact of the vacuous belief assignment. Since PCR5 is presented in details in [13], we just remind PCR5 rule for only two sources⁵: $m_{PCR5}(\emptyset) = 0$ and $\forall X \in G \setminus \{\emptyset\}$

$$m_{PCR5}(X) = m_{12}(X) + \sum_{\substack{Y \in G \setminus \{X\} \\ c(X \cap Y) = \emptyset}} \left[\frac{m_1(X)^2 m_2(Y)}{m_1(X) + m_2(Y)} + \frac{m_2(X)^2 m_1(Y)}{m_2(X) + m_1(Y)} \right] \quad (4)$$

where $m_{12}(X) = \sum_{\substack{X_1, X_2 \in G^\Theta \\ X_1 \cap X_2 = X}} m_1(X_1) m_2(X_2)$ corresponds to the conjunctive consensus on X between the two sources and where all denominators are different from zero and $c(X)$ is the canonical form⁶ of X , i.e. its simplest form (for example if $X = (A \cap B) \cap (A \cup B \cup C)$, $c(X) = A \cap B$). If a denominator is zero, that fraction is discarded.

⁴partial ignorance being the disjunction of elements involved in the partial conflicts.

⁵A general expression of PCR5 for an arbitrary number ($s > 2$) of sources can be found in [13].

⁶The canonical form is introduced here explicitly in order to improve the original formula given in [11] for preserving the neutral impact of the vacuous belief mass $m(\Theta) = 1$ within complex hybrid models. Actually all propositions involved in formulas are expressed in their canonical form, i.e. conjunctive normal form, also known as conjunction of disjunctions in Boolean algebra, which is unique.

3 The ESMS filter

3.1 Purpose of the ESMS filter

The main idea proposed in this paper is to improve the performances of the fusion machine/fusion processor by setting up a pre-processing task in order to select only a subset of sources, called consistent sources, to combine among all sources available at each time-step of the process. Such an idea is very general since it doesn't depend on the application neither on the fusion machine/rule itself (while the belief function framework is used). We will show in the next section of this paper how such an idea can improve the performance results for an autonomous robot navigation application and help to solve more efficiently the SLAM problem. So the basic idea is to keep as feeding input of the fusion machine only sources coherent with respect to a pre-defined similarity measure (see next subsections). Inconsistent sources are discarded by the pre-processor and will not feed the fusion machine. In the sequel, the pre-processor is referred as the Evidence Support Measure of Similarity filter (ESMS filter for short) since the rejection of incoherent sources will be based on the filtering of Measure of Similarity based on Evidential information. The complete improved processing is then done according the following block-scheme:

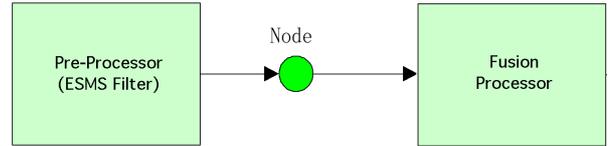


Fig. 2: Improved processing with the ESMS filter

3.2 Some definitions and theorems

Definition 1 (measure of similarity): Let's consider any three gbbas, say $m_1(\cdot)$, $m_2(\cdot)$ and $m_3(\cdot)$ defined over same space G^Θ , the mapping $N(\cdot, \cdot) : G^\Theta \times G^\Theta \rightarrow [0, 1]$ is called an Evidence Support Measure of Similarity (ESMS) or a *similarity function* for short, if the three following conditions are satisfied:

1. $\forall m_1(\cdot), m_2(\cdot), N(m_1, m_2) = N(m_2, m_1)$;
2. $\forall m(\cdot)$ defined over G^Θ , $N(m, m) = 1$;
3. $N(m_1^X, m_2^Y) = 0$ if $X \neq Y$.

where m_s^X , $s = 1, 2$, represents a belief assignment *totally focused* on X , $X \in G^\Theta \setminus \{\emptyset\}$. $m_s^X(\cdot)$ is defined by $m_s^X(X) = 1$ and $m_s^X(Y) = 0$ for all $Y \neq X$.

If $N(m_1, m_2) > N(m_1, m_3)$, then m_2 is said more similar to m_1 than m_3 . $N(m_1, m_2)$ is the *evidence supporting measure of similarity* between $m_1(\cdot)$ and $m_2(\cdot)$.

Theorem 1: If there exists an unitary n -dimensional vector (i.e. a basic belief assignment) $m_1(\cdot)$ and an enough small positive real number ϵ is given, then not

less than one unitary n -dimensional vector $m_2(\cdot)$ exist and satisfy the condition of some distance measure⁷ $d(m_1, m_2) \leq \epsilon$.

Proof (by contradiction): Let's suppose there doesn't exist the vector $m_2(\cdot)$ satisfying the condition $d(m_1, m_2) \leq \epsilon$, then we may let $m_2(\cdot)$ to be equal to $m_1(\cdot)$, so it is known that $d(m_1, m_2) = 0$, but by assumption $\epsilon > 0$, then $d(m_1, m_2) \leq \epsilon$. So it is in conflict with the assertion of theorem and thus this completes the proof by contradiction.

Definition 2 (agreement of evidence) : If there exist two basic belief assignments $m_1(\cdot)$ and $m_2(\cdot)$ defined over the same space G^Θ such that $d(m_1, m_2) \leq \epsilon$, $\epsilon > 0$, for some distance $d(\cdot, \cdot)$, then ϵ is called the *agreement of evidence* supporting measure between $m_1(\cdot)$ and $m_2(\cdot)$ with respect to distance d . $m_1(\cdot)$ and $m_2(\cdot)$ are ϵ -consistent with respect to distance d .

Theorem 2: If there exist two basic belief assignments $m_1(\cdot)$ and $m_2(\cdot)$ defined over the same space G^Θ , then the following sufficient and necessary condition holds:

- if $m_1(\cdot)$ and $m_2(\cdot)$ are ϵ -consistent ($d(m_1, m_2) \leq \epsilon$), then they satisfy Theorem 1.

Proof : We first prove the sufficient condition. Since $m_1(\cdot)$ and $m_2(\cdot)$ are assumed ϵ -consistent, then from definition 2, there exists a small positive real number ϵ , such that $d(m_1, m_2) \leq \epsilon$. So satisfies the theorem 1. Secondly, we prove the necessary condition. From theorem 1, if a basic belief assignment $m_1(\cdot)$ and a small positive real number ϵ are given, then there must exist a basic belief assignment vector $m_2(\cdot)$, which keeps $d(m_1, m_2) \leq \epsilon$, and thus satisfies the definition 2, we think the evidence supporting measure between $m_1(\cdot)$ and $m_2(\cdot)$ is consistent.

Theorem 3: The smaller $\epsilon > 0$ is, the nearer the distance between $m_1(\cdot)$ and $m_2(\cdot)$ is, that is, the more similar or consistent $m_1(\cdot)$ and $m_2(\cdot)$ are.

Proof : According to the theorem 2, if the evidence measure between $m_1(\cdot)$ and $m_2(\cdot)$ is ϵ -consistent, then $d(m_1, m_2) \leq \epsilon$. Let's take $\epsilon = 1 - N(m_1, m_2)$; when ϵ becomes smaller and smaller, $N(m_1, m_2)$ becomes greater and greater, according to the definition of ESMS and thus more similar or consistent $m_1(\cdot)$ and $m_2(\cdot)$ become. Finally, if $\epsilon = 1 - N(m_1, m_2) = 0$, then $m_1(\cdot)$ and $m_2(\cdot)$ are totally consistent.

From the previous definitions and theorems, we propose to use a pre-processing/thresholding technique based on ESMS as an efficient tool to weight the agreement measure of two sources of evidence.

⁷Here we don't specify the distance measure and keep it only as a generic distance. Actually $d(\cdot, \cdot)$ can be any distance measure. In practice, the Euclidean distance is frequently used.

3.3 A simple ESMS function

Definition 3 : Let $\Theta = \{\theta_1, \dots, \theta_n\}$ ($n > 1$), $m_1(\cdot)$ and $m_2(\cdot)$ defined over G^Θ , X_i the i -th (generic) element⁸ of G^Θ and $|G^\Theta|$ the cardinality of G^Θ . A simple ESMS function considered in this work is defined by

$$N_E(m_1, m_2) = 1 - \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{|G^\Theta|} (m_1(X_i) - m_2(X_i))^2} \quad (5)$$

Remark: The ESMS function is not unique and other functions (see [8]) could be used. The one proposed here is simple enough to be used easily in our simulator. The purpose of this paper is not to justify a specific ESMS function, but to show the advantage of the ESMS filter for improving performances of the fusion machine.

Theorem 4: $N_E(m_1, m_2)$ defined in (5) is an ESMS function.

Proof :

1. Let's prove that $N_E(m_1, m_2) \in [0, 1]$. If $N_E(m_1, m_2) > 1$, from (5) one would get $\frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{|G^\Theta|} (m_1(X_i) - m_2(X_i))^2} < 0$ which is impossible, so that $N_E(m_1, m_2) \leq 1$. Let's prove $N_E(m_1, m_2) \geq 0$ or equivalently from (5), $\sum_{i=1}^{|G^\Theta|} (m_1(X_i) - m_2(X_i))^2 \leq 2$. This inequality is equivalent to $\sum_{i=1}^{|G^\Theta|} m_1(X_i)^2 + \sum_{i=1}^{|G^\Theta|} m_2(X_i)^2 \leq 2 + 2 \sum_{i=1}^{|G^\Theta|} m_1(X_i)m_2(X_i)$. We denote it (i) for short. (i) always holds because one has $(\sum_{i=1}^{|G^\Theta|} m_1(X_i)^2 + \sum_{i=1}^{|G^\Theta|} m_2(X_i)^2) \leq ((\sum_{i=1}^{|G^\Theta|} m_1(X_i))^2 + [\sum_{i=1}^{|G^\Theta|} m_2(X_i)]^2)$ and thus $(\sum_{i=1}^{|G^\Theta|} m_1(X_i)^2 + \sum_{i=1}^{|G^\Theta|} m_2(X_i)^2) \leq 2$ because $[\sum_{i=1}^{|G^\Theta|} m_s(X_i)]^2 = 1$ for $s = 1, 2$ ($m_s(\cdot)$ being normalized bba). Therefore inequality (i) holds and thus $N_E(m_1, m_2) \geq 0$.
2. It is easy to check that $N_E(m_1, m_2)$ satisfies the first condition of Definition 1.
3. If $m_1(\cdot) = m_2(\cdot)$, then $N_E(m_1, m_2) = 1$ because $\sum_{i=1}^{|G^\Theta|} (m_1(X_i) - m_2(X_i))^2 = 0$. Thus the second condition of Definition 1 is also satisfied.
4. If there exist m_1^X and m_2^Y for some $X, Y \in G^\Theta \setminus \{\emptyset\}$ such that $X \neq Y$, then according to (5), one gets $\sum_{i=1}^{|G^\Theta|} (m_1(X_i) - m_2(X_i))^2 = [m_1^X(X)]^2 + [m_2^Y(Y)]^2 = 2$ and thus one has $N_E(m_1^X, m_2^Y) = 1 - (\sqrt{2}/\sqrt{2}) = 0$ so that $N_E(\cdot, \cdot)$ verifies the third condition of Definition 1.
5. According to definition 1, we can easily check that $N_E(m_1, m_2)$ is a distance measure between $m_1(\cdot)$ and $m_2(\cdot)$, since according to theorem 3, if there exists $m_3(\cdot)$ such that $N(m_1, m_2) > N(m_1, m_3)$, then m_2 is more similar to m_1 than m_3 .

⁸The order on G^Θ doesn't count and we don't consider here \emptyset as an useful element of G^Θ because its belief mass is always set to zero in our approach.

3.4 Barycentre of belief masses

We introduce here the barycentre of belief masses which will be used in the ESMS filter. The ESMS filter will reject all sources having an ESMS value (5) below a pre-defined rejection threshold chosen by the system designer. We must distinguish two cases for the derivation of the barycentre of belief mass depending on the reliability of the sources.

3.4.1 Case 1: Equireliable sources

Let's denote $k = |G^\Theta|$ the cardinality of G^Θ and consider S independent⁹ sources of evidence. If all sources are equireliable, the barycentre of belief masses of the S sources is given by: $\forall j = 1, \dots, k$

$$\bar{m}(X_j) = \frac{1}{S} \sum_{s=1}^S m_s(X_j) \quad (6)$$

Theorem 5: The vector of barycentres of belief masses is also a belief mass, i.e. $\sum_{j=1}^k \bar{m}(X_j) = 1$

Proof: We use the matrix representation \mathbf{M} for the set of all gbba where the index of each row of \mathbf{M} corresponds to a specific source and the index of each column of \mathbf{M} corresponds to a specific element of G^Θ . For example, for S sources with $k = |G^\Theta|$, one has

$$\mathbf{M} = \begin{bmatrix} m_1(X_1) & m_1(X_2) & \dots & m_1(X_k) \\ m_2(X_1) & m_2(X_2) & \dots & m_2(X_k) \\ \vdots & \vdots & \dots & \vdots \\ m_S(X_1) & m_S(X_2) & \dots & m_S(X_k) \end{bmatrix}$$

The sum of each row of \mathbf{M} is one since each source is characterized by its own (normalized) gbba, so that the total sum of all elements of \mathbf{M} is S . Therefore, the sum of all the sums of each column of \mathbf{M} is also S and thus the total sum of normalized sums (normalization by S) of each column (i.e. the sum of barycentres of each column) is one, which completes the proof.

3.4.2 Case 2: Unreliable sources

We consider each source s with its reliability factor $\alpha_s \in [0, 1]$. The gbba of each source is discounted with the classical discounting method [10, 3, 4, 15, 11]

$$\begin{cases} m'_s(X) = \alpha_s m_s(X), & \forall X \in G^\Theta, X \neq \Theta \\ m'_s(\Theta) = (1 - \alpha_s) + \alpha_s m_s(\Theta) \end{cases}$$

where Θ denotes here the proposition reflecting the total ignorance, i.e. $\Theta = \theta_1 \cup \theta_2 \cup \dots \cup \theta_n$.

The barycentre of (discounted) gbba is expressed as previously, i.e. $\forall j = 1, \dots, k$

$$\bar{m}'(X_j) = \frac{1}{S} \sum_{s=1}^S m'_s(X_j) \quad (7)$$

⁹Although independence is a difficult concept to define in all theories managing epistemic uncertainty, we consider that two sources (or more) of evidence are independent (i.e. distinct and noninteracting) if each leaves one totally ignorant about the particular value the other will take.

Similarly to Theorem 5, one has $\sum_{j=1}^k \bar{m}'(X_j) = 1$. In fact, we may regard easily the same reliable degree as a special instance, when discounting/reliability factor α_i is equal to one.

3.5 Principle of the ESMS filter

Let's consider a frame Θ , n discernable "objects" in the system and $S > 1$ sources of evidence. The principle of the ESMS filter, corresponding to the left block in Fig. 2, is represented by Fig. 3 where s_1, s_2, \dots, s_S represent the S sources of evidence available as inputs to the pre-processor, i.e. the ESMS filter. o_1, o_2, \dots, o_n express n discernable objects. $s_i(o_j)$ represents the belief mass assignment defined on G^Θ provided by the i -th source of evidence about the j -th discernable object. s_{aj} represents the vector of barycentres of each proposition in G^Θ for the j -th object computed from belief masses of the sources of evidences. s_{aj} is computed according to the formula (6) (or (7) if sources are not considered as equireliable and reliability factors are known). $N_{Ei}(o_j)$ represents the ESMS between the barycentre of belief mass and the belief mass $m_i(\cdot)$ of the i -th source committed to the j -th discernable object. $N_{Ei}(o_j)$ is computed according to (5). $N(o_j) = 1 - \epsilon$ is the rejection threshold for the ESMS filter (i.e. the ϵ -consistency tuning parameter), which is a positive real number in $[0, 1]$ chosen by the system designer. When the condition $N_{Ei}(o_j) > N(o_j)$ is satisfied, the pre-processed information can pass through the ESMS filter and thus the corresponding source can feed the fusion machine (right block in Figure 2). Node(i) expresses the connecting node between the ESMS filter and the fusion machine.

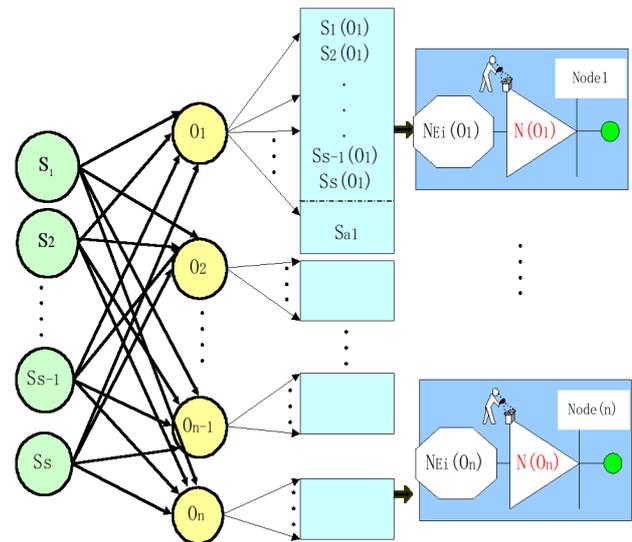


Fig. 3: Principle of the ESMS filter

3.6 Example

Let's consider a 2D-frame $\Theta = \{\theta_1, \theta_2\}$, ten equireliable sources with bba listed in Table 1 and let's work on $G^\Theta \equiv D^\Theta = \{\emptyset, \theta_1 \cap \theta_2, \theta_1, \theta_2, \theta_1 \cup \theta_2\}$

	$\theta_1 \cap \theta_2$	θ_1	θ_2	$\theta_1 \cup \theta_2$	N_E
$m_1(\cdot)$	0.2	0.3	0.4	0.1	0.8735
$m_2(\cdot)$	0.4	0.3	0.2	0.1	0.8000
$m_3(\cdot)$	0.2	0.4	0.1	0.3	0.8268
$m_4(\cdot)$	0.1	0.7	0.1	0.1	0.7592
$m_5(\cdot)$	0.1	0.1	0.8	0.0	0.5550
$m_6(\cdot)$	0.2	0.5	0.2	0.1	0.9106
$m_7(\cdot)$	0.1	0.4	0.3	0.2	0.9368
$m_8(\cdot)$	0.2	0.3	0.1	0.4	0.7592
$m_9(\cdot)$	0.1	0.4	0.5	0.0	0.8103
$m_{10}(\cdot)$	0.0	0.8	0.1	0.1	0.6806
S_a	0.16	0.42	0.28	0.14	1.0000

Table 1: Sources for the ESMS filter

The values of N_E and S_a have been obtained using formulas (5) and (6) respectively. Now let's assume that the ESMS threshold is set to 0.75 by the system designer, then from the Table 1, one can see that the sources no 5 and 10 will be automatically filtered and discarded (and thus they will not enter in the fusion process) because their corresponding N_E values are below the ESMS threshold. If the ESMS threshold is set to 0.80, then the sources no. 4, 5, 8 and 10 will be filtered and discarded. That is, the higher is the ESMS threshold, the less is the number of information sources available to feed the fusion processor.

3.7 Remarks

The proposed approach using the ESMS filtering techniques for the validation of consistent sources to combine presents the two following main advantages :

1. The ESMS filter saves significantly the computational cost for real-time system, even if at first glance one would think the contrary. In fact, at the fusion level and because of the ESMS filter, only a smaller number of sources have to be combined actually; especially, when many sources carrying redundant and conflicting information appear in the system, its predominance is more obvious. Such situation happens when the robot runs in the environment since some grid-cells can be scanned either by different sensors or by the same sensor at different times (at same or different locations). Therefore, due to the uncertainty, the datum from sensors can become redundant or conflicting at the same time.
2. The ESMS filter allows to improve the precision and correctness of the fusion result since all inconsistent sources have been efficiently discarded.

The ESMS filtering approach increases the popularity of the evidence reasoning methods and enlarge the range of application for some models. It doesn't depend on the Fusion machine/rule since it is a preprocessing task for keeping away all inconsistent sources

outside the fusion process itself. It can be seen as a preventing tool for avoiding the combination of incoherent sources of evidence (modeled by normalized belief functions), which otherwise could rise to very bad and unexpected results (depending obviously of the type of Fusion machine used in the system). The ESMS filter doesn't fit within TBM framework since one works only with normalized belief function here.

4 Simulation results for SLAM

Self Localization And Mapping (SLAM) is a very hot and difficult problem in robotics since it can be compared to the puzzle of the egg and the chicken. To evaluate the benefit of the ESMS filter, we have carried on simulations (with and without the ESMS filter) for solving the SLAM problem with a virtual Pioneer II mobile robot and DSmT-based fusion machine running PCR5 fusion rule. Here self localization mainly depends on the odometer on the robot in our simulation experiment. Of course, we also may choose other sensors (i.e. sonar, laser, and vision etc) in real environment with respect to the imprecise odometer measurement to improve the precision of localization. Map building is an important loop in SLAM. Here we mainly compare the result of map building with and without the ESMS filter. The experiment consists in simulating the autonomous navigation of a virtual Pioneer II Robot carrying 16 simulated sonar detectors in a 5000mm×5000mm square array with a unknown obstacle/object. The map building with sonar sensors on the mobile robot is done from the simulator of SRIsim of ActivMedia company coupled with our self-developing experimental or simulation platform (see Fig. 4 and 5).

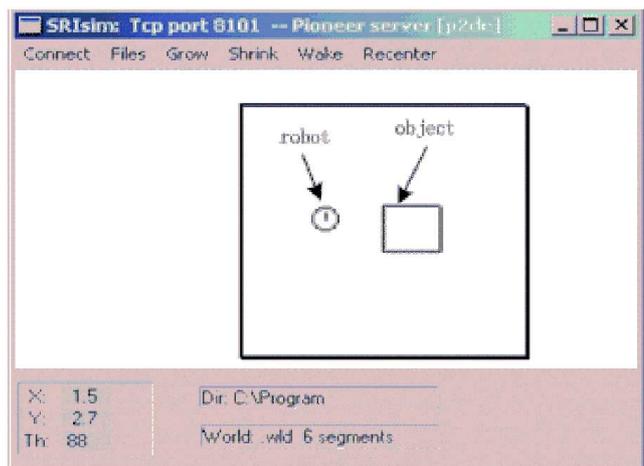


Fig. 4: A world map opened in the SRIsim

The platform was developed under Visual C++ 6.0 and OpenGL server as a client end, which allows to connect the server end (also developed by ourselves, which connects the SRIsim and the client). When the virtual robot runs in the virtual environment, the server end collects many information (i.e. the location of robot, sensors measurements, velocity, etc) from the

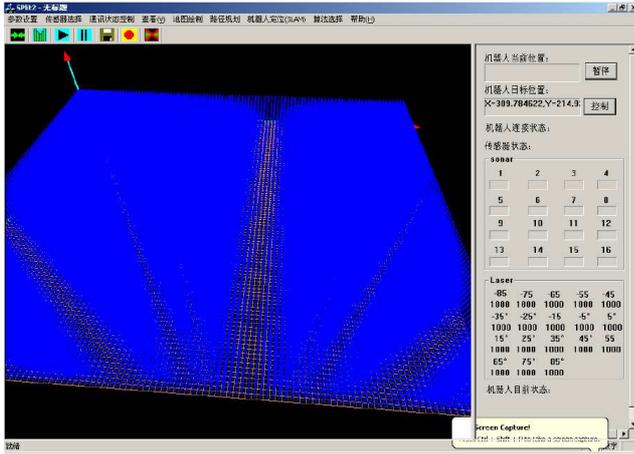


Fig. 5: Platform for simulation or real experiment

SRIsim. Through the TCP/IP protocol, the client end can get any information from the server end and fuse them. The Pioneer II Robot may begin to run at arbitrary location; here we choose the location (1500mm, 2700mm) with a 88 degrees angle the robot faces to. We let the robot move at speeds of trans-velocity 100mm/s and turning-velocity 50degree/s around the object in the world map plotted by the Mapper (plotting software), which is opened in the SRIsim as in Fig. 4. There are many methods in map building, here we adopt grid method to build map. The global environment is divided into 50×50 lattices (with same cell size). The object in Fig. 4 is taken as a regular rectangular box. When the virtual robot runs around the object, through its sonar sensors, we can clearly recognize the object and estimate its appearance, and even its location in the environment. The sequential DSMT/PCR5 fusion machine was used in our simulation based on the frame $\Theta = \{\theta_1, \theta_2\}$ where θ_1 means that the grid-cell under consideration is empty while θ_2 means that the grid-cell is occupied by an obstacle. Then we can define and derive a belief assignment $m(\theta_1 \cap \theta_2)$, $m(\theta_1)$, $m(\theta_2)$ and $m(\theta_1 \cup \theta_2)$ from each sensor measurement which will be fused by PCR5 rule. Due to space limitation, we cannot go in details here and we refer to [5] for a complete presentation of derivation of belief masses $m(\cdot)$. The ESMS filter is taken as pre-processor of fusion, which can filter the inconsistent sources and make evidence more consistent. In this experiment, the ESMS filtering threshold was set to 0.7. The choice of the threshold depends highly on the real system and is left to the system designer. In our simulation we have assumed that all sonar sensors had the same characteristics and same reliability. The sampling period for measurements was 100 ms. Here are the main steps involved in the simulator:

1. Initialize the parameters of the robot (its location, velocity, etc).
2. Acquire 16 sonar measurements (and robot's location when the robot is running)
3. Compute the belief masses of the fan-form area detected by each sonar sensor.

4. If some grid-cells are scanned more than 5 times by sonar sensors (same sonar in different location or different sonar sensors) go to next step otherwise go back to step 2.
5. All of 5 evidence sources enter into the ESMS filter; the inconsistent information is filtered, then the remaining consistent sources of evidence feeds the sequential fusion machine if at least two sources are consistent enough, otherwise go back to step 2 to acquire new sources of evidence.
6. Compute the credibility of occupancy $Bel(\theta_2)$ of all grid-cells which have been fused.
7. Rebuild the map of the environment for this sampling period and go back to step 2 until all grid-cells have been explored and updated.

The deduced world maps obtained by our simulator are shown in Fig. 6 and Fig. 7 when the mobile robot moves around the object. The vertical axis corresponds to the credibility of occupancy of the cells, i.e. $0 \leq Bel(\theta_2) \leq 1$. The higher is $Bel(\theta_2)$, the higher is the belief that the cell is occupied by an object. X and Y axis provide the coordinates of the grid-cells. Fig. 6 is the result of the PCR5-based fusion machine without the ESMS filter and Fig. 7 shows the result with the same fusion machine coupled with the ESMS filter.

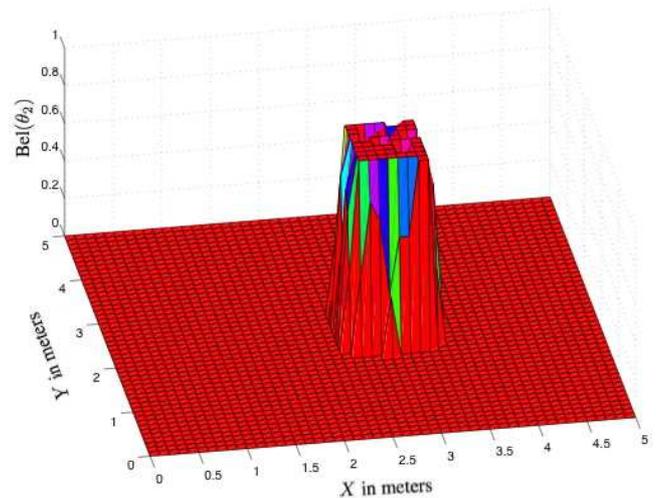


Fig. 6: Map reconstruction without the ESMS filter

According to our first results presented in Fig. 6 and Fig. 7, one concludes that :

1. The map reconstruction obtained by the fusion machine with the ESMS filter is better than the map reconstruction obtained by the fusion machine without the ESMS filter) since the brim of object in world map is clearer and more regular in Fig. 7 than that in Fig. 6.
2. The fusion time is short, although in our simulations, the time spent by the two methods is no obviously different, this is because there are no enough evidence sources, although the system may

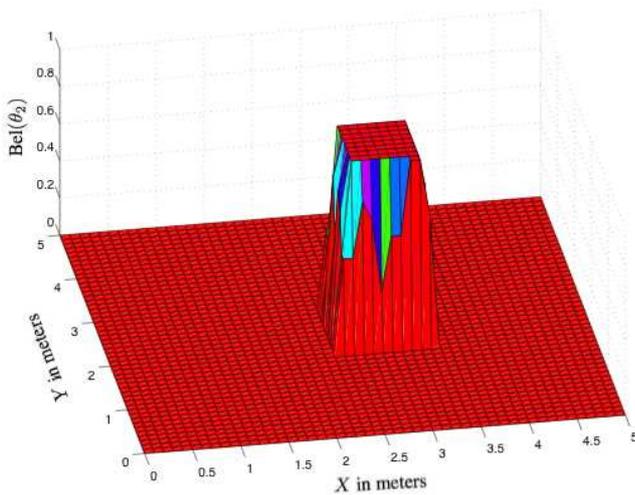


Fig. 7: Map reconstruction with the ESMS filter

supply with many evidence sources. When we fuse them, in order to compute simply, we restrict the maximum numbers of evidence sources is less than 5. In fact, if we don't restrict the number of evidence sources in the robot system, or increase the number, then we believe, the fusion time will be obviously short.

3. Since the number of sources of evidence which can pass through the ESMS filter is less than the feeding input number, especially when many inconsistent sources are filtered and discarded, the computing amount is very low; The fusion machine only fuses useful/consistent information.

5 Conclusion

We have proposed a general pre-processor (the ESMS filter) to any fusion machine working with sources of evidence based on normalized basic belief functions. Thanks to a simple thresholding method, the ESMS filter eliminates the sources which are inconsistent with the barycentre of belief masses. The approach is target-based, not sensor-based, just when considering the mutually-complemental information from dissimilar sensors, we can't use this method to filter the discordant information simply. Under this condition, we only can reserve the discordant information temporarily, and then deal with them at decision level. Our approach has been validated in simulation with a Pioneer II mobile robot. The PCR5-based fusion machine coupled with the ESMS filter improves the precision of the map reconstruction and reduces the computation burden. This work shows the ability of a DSMT-based fusion machine to solve a challenging SLAM problem. Although PCR5 with the ESMS filter provides very good results in our simulations, we expect to improve the performances using a new PCR6-based fusion machine coupled with the ESMS filter, since the PCR6 fusion rule proposed recently by Martin and Osswald is more intuitive and efficient for the fusion of $s > 2$ sources than PCR5 or other classical fusion rules.

References

- [1] Daniel M., *Distribution of Contradictive Belief Masses in Combination of Belief Functions*, Information, Uncertainty and Fusion, Acad. Publishers, pp.431-446, 2000.
- [2] Dezert J., Smarandache F., *DSmT: A new paradigm shift for information fusion*, in Proc. of Cogis'06 Conf., Paris, March 2006.
- [3] Dubois D., Prade H., *Representation and combination of uncertainty with belief functions and possibility measures*, Comp. Intell., 4, pp. 244-264, 1988.
- [4] Lefèvre E., Colot O., Vannoorenberghe P., *Belief functions combination and conflict management*, Inf. Fusion J., Vol. 3, No. 2, pp. 149-162, 2002.
- [5] Li X., Huang X., Wang M., *Robot Map Building from Sonar Sensors and DSmT*, Inf. & Sec.: An Int. J., Bulg. Acad. of Sci., Sofia, Vol. 20, May 2006.
- [6] Martin A., Osswald C., *A new generalization of the proportional conflict redistribution rule stable in terms of decision*, in [12].
- [7] Pan Quan P. and al., *Essential Methods and Progress of Information Fusion Theory*, Acta Automatica Sinica, Vol. 29, No.4, pp. 599-615, July 2003.
- [8] Ristic B., Smets Ph., *Association of Uncertain Combat ID Declarations*, in Proc. of Cogis'06 Conf., Paris, March 2006.
- [9] Sentz K., Ferson S., *Combination of evidence in Dempster-Shafer Theory*, SANDIA Tech. Report, SAND2002-0835, 96 pages, April 2002.
- [10] Shafer G., *A Mathematical Theory of Evidence*, Princeton University Press, Princeton, NJ, 1976.
- [11] Smarandache F., Dezert J. (Editors), *Applications and Advances of DSmT for Information Fusion*, Amer. Res. Press, Rehoboth, 2004, <http://www.gallup.unm.edu/~smarandache/DSmT-book1.pdf>.
- [12] Smarandache F., Dezert J. (Editors), *Applications and Advances of DSmT for Information Fusion*, Vol. 2, Amer. Res. Press, Rehoboth, July 2006.
- [13] Smarandache F., Dezert J., *Proportional conflict redistribution rules for information fusion*, in [12].
- [14] Smarandache F., Dezert J., *Information Fusion Based on New Proportional Conflict Redistribution Rules*, Proc. of Fusion 2005, July 2005.
- [15] Smets Ph., *Data Fusion in the Transferable Belief Model*, Proc. of Fusion 2000, Paris, July 2000.
- [16] Yager R.R., *On the Dempster-Shafer Framework and New Combination Rules*, Inf. Sci., Vol. 41, pp.93-138,1987.