

A MES Pre-processor Design in Multi-source Information Fusion

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Abstract: In multi-sources information fusion, because of the diversity of evidences, especially the imperfect evidences, it's difficult to get a satisfied result. To avoid and reduce the influence of the mistaken or conflicting information on the final precision of fusion, a pre-processor of evidence sources is proposed and proved. A MES (measurement of evidence support) pre-processor is designed. Firstly, the reliability of every evidence source is analyzed from itself generalized basic belief assignment (gbba) to identify the centre of the whole evidence sources. Then the distance measurement between every evidences and the centre evidence is confirmed according to the relation support. The identification algorithm of computing reliability is also presented. The evidence source with larger distance won't be sent into the fusion to achieve the faster and more precise information result. Finally we apply the new tool coupling with the fusion rule based on Dezert and Smarandache Theroy (DSmT) to P2DX robot perception. Experiment results show the effectiveness and robustness of this method.

Keywords: multi-source information; pre-processor of evidence sources; DSmT; reliability

Introduction

During the research and development in information fusion for nearly 20 years, people tend to focus on the fusion algorithms. And few is concerned on the main of fusion—evidence sources. In practice, taking into account the imperfect (incomplete, inaccurate, uncertain, inconsistent) evidence sources in the multi-source information fusion, its influence to the fusion results is quite different. A mistake evidence source will lead the fusion to a fault or even an absurd result. In the past, people attempted to improve the fusion algorithm. Although there had been some partial achievement, they weren't satisfied. Philosophical view believed that the method X solving the model Y had an absurd result Z. It couldn't be sure that the method X was error. It was also possible that the model Y is not correct. [1][2] proposed the concept of a distance to measure the influence resulted by the evidence sources. [3][4] built the ESMS (evidence supporting measure of similarity) filter before fusion. The evidence sources with high consistent would be selected to the fusion. However its center of the evidence sources obtained through the gbba arithmetic average of all the evidence sources. It didn't fully reflect the distribution of the evidence sources. The distance measurement used a simple Euler

distance. It didn't fully reflect the internal relationship between the attributes of the evidence sources either. Based on the above shortcomings, the gbba of the evidence sources themselves is adopted to determine the reliability of the evidence sources. At the same time the method calculating the centre of the imperfect evidence sources is given. Combined with the concept of super-power set in the Dezert and Smarandache Theroy (DSmT)^[5] and the Venn diagram, a positive matrix describing the internal relationships between the attributes evidence sources is provided. Finally an objective distance measurement is obtained about the internal relationship between the attributes. The study improves the problem about absolutism and experience in the past. Experiences further show that this method is effective and robust.

Review of relative theories

Notion of hyper-power set D^Θ : Let $\Theta = \{\theta_1, \dots, \theta_n\}$ be a finite set (called frame) of n elements. The hyper-power set D^Θ ^[6] is defined as the set of all composite propositions built from elements of Θ with \cup and \cap operators such that:

$$a) \phi, \theta_1, \dots, \theta_n \in D^\Theta ;$$

- b) If $A, B \in D^\ominus$, then $A \cap B \in D^\ominus$
and $A \cup B \in D^\ominus$;
- c) No other elements belong to D^\ominus , except those obtained by using rules a) or b).
- (1)

Generalized belief functions: We define a map from a general frame Θ $m(\cdot): D^\ominus \rightarrow [0,1]$ associated to a given source, say B , of evidence as

$$m(\phi) = 0 \quad \text{and} \quad \sum_{A \in D^\ominus} m(A) = 1 \quad (2)$$

The quantity $m(A)$ is called the *generalized basic belief assignment/mass* (gbba) of A .

The generalized belief and plausibility functions are defined as

$$\begin{aligned} Bel(A) &= \sum_{\substack{B \subseteq A \\ B \in D^\ominus}} m(B) \\ Pl(A) &= \sum_{\substack{B \cap A \neq \phi \\ B \in D^\ominus}} m(B) \end{aligned} \quad (3)$$

If the discernment framework is looked as a set of possibility, then the belief function shows the belief degree of possibility and the plausibility function shows the no doubt degree of possibility.

Classic DSm Rule for Free-DSm Model : For k independent uncertain and paradoxical sources of information providing generalized basic belief assignment $m_i(\cdot)$ over D^\ominus , the classical DSm conjunctive rule of combination $m_{M^f(\Theta)}(A)$ is given by [7]

$$\forall A \in D^\ominus, \quad m_{M^f(\Theta)}(C) = \sum_{\substack{A_i, B_j \in D^\ominus \\ A_i \cap B_j = C}} m_1(A_i) m_2(B_j) \quad (4)$$

Concept of u_n and D_n : u_n is the cardinary of the hyper-power set. D_n is the coefficient matrix of the hyper-power set based on u_n [8].

Let $u_n = [u_1, u_2, \dots, u_{2^{n-1}}]$ base on a recursive construction starting with

$u_1 = [< 1 >]$. Having constructed u_{n-1} , then we can construct u_n for $n > 1$ recursively as follows:

- include all elements of u_{n-1} into u_n ;
- afterwards, include element $< n >$ as well in u_n ;

• then at the end of each element of u_{n-1} concatenate the element $< n >$ and get a new set u'_{n-1}

which then is also included in u_n .

Matrix D_n which can be easily obtained by the following recursive procedure:

- start with $D_0^c = [0 \ 1]$ corresponding to all Boolean functions with no input variable ($n = 0$).
- build the D_1^c matrix from each row r_i of D_0^c by adjoining it to any other row r_j of D_0^c such that $r_i \cup r_j = r_j$. Since the tautology is not involved in the hyper-power set, then one has to remove the first column and the last line of

$$D_1^c = \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 1 \end{bmatrix} \quad \text{to obtain finally} \quad D_1 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

- build D_2^c from D_1^c by adjoining to each row r_i of D_1^c , any row r_j of D_1^c such that $r_i \cup r_j = r_j$ and then remove the first column and the last line of D_2^c to get D_2 .

- build D_3^c from D_2^c by adjoining to each row r_i of D_2^c any row r_j of D_2^c such that $r_i \cup r_j = r_j$ and then remove the first column and the last line of D_3^c to get D_3 given by

- Likewise, D_n^c is built from D_{n-1}^c by adjoining to each row r_i of D_{n-1}^c any row r_j of D_{n-1}^c such that $r_i \cup r_j = r_j$. Then D_n is obtained by removing the first column and the last line of D_n^c .

MES Pre-processor designed before fusion

The Centre of N Evidence Sources: Assume that there are N evidence sources with E_1, E_2, \dots, E_N . Discernment framework is as Θ , factor of weight is defined as w_k of evidence source E_k ($k = 1, 2, \dots, N$). According to the definition about the Bel () and Pl () function in formula (3), the interval [Bel (), Pl ()] means that the uncertainty of the evidence source. The uncertainty of i evidence source is defined as r_k as following:

$$r_k = \frac{Bel(E_k)}{Pl(E_k)} \quad (5)$$

The weight of i evidence source is defined as w_k as following:

$$w_k = \frac{r_k}{\sum_{k=1}^N r_k} \quad (6)$$

The evidence source with the higher uncertainty will occupy the less weight during calculating the centre of the evidence sources. On the other hand, the lower uncertainty will cause the higher weight. This is similar to person's intuitive. The more uncertainty of evidence source provides the less useful information and the lower reliability of the evidence source. On the contrary, the less uncertainty the evidence source is, the more information provide and the higher reliability of the evidence sources. As a result, the centre of the evidence sources will be got based on the weighted average of the gbba of the evidence itself uncertainty instead of the arithmetic average.

Assume that all N independent evidence sources are reliable, and then the centre of N evidence sources is expressed as follows:

$$m^*(A_i) = \sum_{k=1}^N w_k m_k(A_i) \quad (7)$$

in which $A_i \in D^\Theta$

Definition of the $s(\cdot)$ function [7] [9]: $s(\cdot)$ is based on a very simple and natural geometrical interpretation of the relationships between the parts of the Venn diagram belonging to each $\theta_i \in D^\Theta$. All the values of the $s(\cdot)$ function (stored into a vector s) over D^Θ are defined by

the following equation: $s = D_n \cdot \omega_n$. The components ω_i of vector ω_n are obtained from the components of the DSsm encoding basis vector u_n .

$$\omega_i = \frac{1}{l(u_i)} \quad (8)$$

where $l(u_i)$ is the length of

Smarandache's codification u_i .

Measurement of Evidence Support (MES):

The key in the information fusion is the reliability of every evidence source. The relationship between the evidence sources will also affect the results of the information fusion. In view of this situation, matrix $s(\cdot)$ is introduced to express the relationship between the focus elements in the hyper-power set. A distance is defined to estimate the measurement of evidence support between each evidence source and the centre evidence source. The smaller distance means the higher reliability and the more important to the final result of the fusion, and vice versa. The evidence sources with larger distance will filter to not in the fusion. A threshold of the distance can be defined according to the practice. So only the evidence sources with the more important to the fusion result can come into the fusion after the pre-processor. They will result in the less computation and more precise by less evidence sources with high quantity.

Definition: Let m^* and m be two gbba on the same frame of discernment Θ , containing N mutually exclusive and exhaustive hypotheses. The distance between m^* and m is:

$$d(m^*, m) = \sqrt{\frac{1}{2} (\overline{m^*} - \overline{m})^T \underline{S} (\overline{m^*} - \overline{m})} \quad (9)$$

Where $\overline{m^*}$ is the gbba of the centre evidence source and \overline{m} are the gbba of every evidence source according to formula (2) and \underline{S} is an $|D^\Theta| \times |D^\Theta|$ matrix whose elements are:

$$S(A_i, A_j) = \frac{s[A_i \cap A_j]}{s[A_i \cup A_j]} \quad (10)$$

$$A_i, A_j \in D^\Theta$$

Note that a factor 1/2 is needed in formula

(9) to normalize d and to guarantee that $0 \leq d(m^*, m) \leq 1$.

From Definition of the MES, another way to write d is:

$$d(m^*, m) = \sqrt{\frac{1}{2} (\|\vec{m}^*\|^2 + \|\vec{m}\|^2 - 2\langle \vec{m}^*, \vec{m} \rangle)} \quad (11)$$

where $\langle \vec{m}^*, \vec{m} \rangle$ is the scalar product

defined by

$$\langle \vec{m}^*, \vec{m} \rangle = \sum_{i=1}^{|D^\ominus|} \sum_{j=1}^{|D^\ominus|} m^*(A_i) m(A_j) \frac{A_i \cap A_j}{A_i \cup A_j} \quad (12)$$

with $A_i, A_j \in D^\ominus$ for $i, j = 1, \dots, |D^\ominus|$.

$\|\vec{m}\|^2$ is then the square norm of

$$\vec{m} : \|\vec{m}\|^2 = \langle \vec{m}, \vec{m} \rangle$$

It's easy to verify that the definition of $d(m^*, m)$ satisfies the following requirements for any m_1 and m_2 :

1. Nonnegativity: $d(m_1, m_2) \geq 0$
2. Nondegeneracy:
 $d(m_1, m_2) = 0 \Leftrightarrow m_1 = m_2$
3. Symmetry: $d(m_1, m_2) = d(m_2, m_1)$
4. Triangle inequality:
 $d(m_1, m_2) \leq d(m_1, m_3) + d(m_3, m_2)$

So it's sure that the $d(m^*, m)$ could describe the relationship between every evidence source and the centre evidence source well to show the reliability of every evidence source.

Simulation

Pioneer 2-DXe mobile robot is used in experiment, which is shown as Fig.1. The Pioneer II mobile robot that we use in experiments has 16 sonar sensors. The distribution of sonar sensors is shown as Fig. 2. First of all, the map of a room (size: 8×8 meters) is created. The structure of the room and the original position is shown as Fig.3 to build the environment map. The point of robot is treated as the coordinate origin of the global map. So robot

is set to the pose of $(0,0,0^\circ)$. The third parameter is the deflection angle of robot.



Fig.1. Pioneer 2-DXe mobile robot

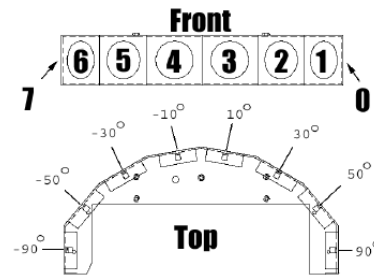


Fig.2. Distribution of front sonar sensors on Pioneer 2-DXe

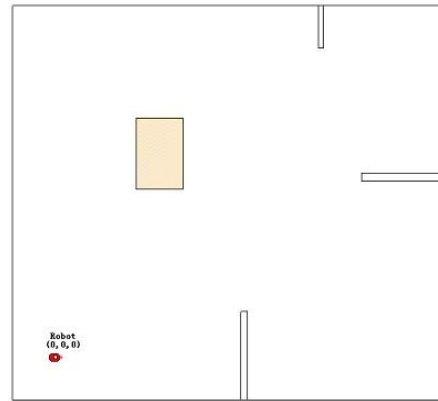


Fig.3. Room structure and the Initial positions of the robot

Suppose there are two elements O and E in the frame of discernment Θ [10].

E means the point in map is empty, O means occupied, the hyper-power set is $D^\ominus = \{\phi, O, E, O \cap E, O \cup E\}$. Then we define $m(E)$ as the general basic belief assignment

functions (gbba) for the empty status, define $m(O)$ as the gbba for occupied status, $m(O \cap E)$ is defined as the gbba of conflict mass, and $m(O \cup E)$ is defined as the gbba of unknown status (it mainly refers to those areas that still not be scanned at present).

Before robot exploring the environment, we propose the map is entirely unknown, that means $m(O \cup E) = 1$ [11]. The result is shown as Fig.4 and Fig5.

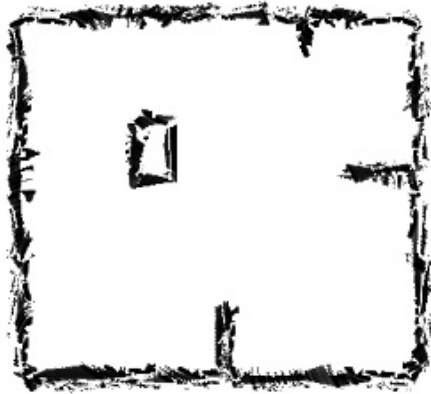


Fig. 4. Map build by DSMT classic rule with MES



Fig. 5. Map build by DSMT classic rule with ESMS

Comparing with the results, the accuracy

of the fusion algorithm with MES is higher than that of algorithm with ESMS, especially on the corner of the walls. During the simulations, the difference is not very clear with the time spending by the two ways. But when it's in the complicated environment or the conflict mass changes frequently, or there is a lot of information with high conflict, the advantages of MES pre-processor with high efficiency can be turned into reality. In one word, the performance of MES is superior to ESMS.

Conclusion

The new MES pre-processor would give a more precise and effective result. This is due to a combination in the MES pre-processor of the reasonable centre evidence source, the mutual support relationship matrix and the distance measurement of evidence support in the fusion. The centre of the evidence sources shows the distribution on the belief degree of all the evidence sources. A positive matrix is adopted to fully reflect the internal relationship between the attributes of the evidence sources. A distance between each evidence source and the centre evidence source is defined as MES to estimate the measurement of evidence support. The identification algorithm is proposed and the properties of this distance are analyzed. The MES respects all the properties respected of a distance and is an appropriate measure of the difference or the lack of similarity between any two evidences. With the MES, the ultimate fusion result is more reasonable and the result is more persuasive.

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