A Weighted Evidence Combination Method for Multisensor Data Fusion

Yin Liu[1], Yang Zhang[2*]

[1] College of Engineering, Peking University, China
[2] Key Laboratory of Communication and Information Systems, Beijing Municipal Commission of Education, School of Electronic and Information Engineering, Beijing Jiaotong University, China
liuyin@stu.pku.edu.cn, zhang.yang@bjtu.edu.cn

Abstract

Multisensor information fusion exerts a key part in lots of practical usages. Dempster-shafer evidence theory has drawn extensive attention in many scopes of information fusion due to its flexibility and effectiveness in dealing with uncertain data without aforehand data. But when combining highly contradictory evidence with Dempster's combinatorial principles, it can result in counterintuitive results. To solve the issue, the study proposes a multi-sensor data weighted evidence combination fusion method based on inter-evidence difference measure. Firstly, different measures including evidence distance and conflict are with the definition of characterizing distinctions between the two pieces of evidence. Then, according to the difference between each evidence and the average evidence, the weight coefficients of each evidence are calculated. In the end, initial evidence is discounted according to weighting factor, as well as Dempster's combination principle is adopted to discount the evidence for fusion. Many instances show that this way can efficiently treat highly conflicting evidence and has good convergence performance.

Keywords: Data fusion, Evidence theory, Conflicting evidence, Dissimilarity measure

1 Introduction

Multisensor data fusion is the technique which combines information offered via multiple sensors into consistent consequences [1]. In the past decades, multisensor information fusion has drew much attention and has been widely applied in many fields, like pattern recognition [2], decision making [3], fault diagnosis [4], supplier management [5], reliability evaluation [6], etc. [7-9]. In practical applications, sensors are easily affected by complex physical environment and their own performance. Local decisions obtained of every sensor are usually inaccurate, fuzzy and indeterminate [10]. For the sake of solving this problem, many math theories are talked over and applied to treat indeterminate, fuzzy as well as inaccurate sensor data. These theories contain Bayesian principle [11], fuzzy set principle [12], Rough set [13], evidence theory [14], evidential reasoning [15], Z number [16], D number [17], etc [18-20]. In this study, we mainly study the evidence theory was on behalf of belief function to treat multi-sensor information fusion.

In 1967, evidence theory was primary suggested by Dempster [21]. He derived and defined top and bottom limitations of possibility under multi-valued mappings. Later, Shafer reinterpreted top and bottom limitations of possibility with trust function in 1976, and extended and developed into a relatively complete theoretical system [22]. Therefore, evidence theory can also be called Dempster-Shafer (DS) theory. Through study and exploitation of numerous scholars, evidence theory has been an entire group of indeterminate reasonable principle, which offers a forceful math instrument for various indeterminate information fusion. In the models of evidence process, any suggestion can include more than one hypothesis. Meanwhile, a value between 0 and 1 is provided for every proposition, indicating the reliability of the proposition. The reliability can be obtained by analyzing the observed information. In addition, the integration of multiple evidence bodies reduces the credibility of unlikely propositions and preserves the most likely propositions as results. But due to the indeterminate or incomplete data gathered by different sensors, there may be a large conflict among sensors for the identical observation, and the D-S evidence theory has a poor fusion effect on conflicting evidence. If large conflicts among initial sources of evidence exist, or the reliability of the sources of evidence is low, use of Dempster's combination principle could result in results opposite to the truth.

In view of the problem, two different methods are proposed to deal with the conflicts between the evidence, namely, improving combniantion principles as well as modifying evidence itself [23]. On the one hand, the method of correcting the evidence itself is to treat contradictory sources as unreasonable evidence and determine the credibility of different evidence [24] according to the degree of conflicts among them. Degree of credibility can indicate degree of truthfulness of a particular source of evidence, or a specific piece of evidence. The more credible a source or evidence is, the more it contributes to the final result and therefore more weight needs to be given to that evidence. Correspondingly, the less credible the source or evidence is, the less weight should be given to it. Then, the obtained weights are applied to modify the original evidence to reduce the influence of the evidence containing large conflicts, and make the fusion result more accurate. On the other hand, the improvement method of evidence combination rules believes that conflicts are caused by unreasonable combination rules, and in order to eliminate conflicts, the combination method needs to be changed [25]. In the process of data fusion, for

*Corresponding Author: Yang Zhang; E-mail: zhang.yang@bjtu.edu.cn
DOI: 10.53106/160792642022052303013

each focal element there is a belief function and a plausibility function. The part between these two functions is the confidence interval, and the evidence in the confidence interval is the conflict part, which cannot be determined accurately in fusion. In the procedure of using D-S evidence principle, due to lack of prior probability, this part of confidence cannot be accurately assigned to a focus element in the frame of discernment. It is Dempster's rule that cannot reasonably allocate conflicting data that leads to abnormal fusion results. To improve the combination rules is to change the traditional Dempster's combination rule, using some new combination rules, redistributing the conflicts in the evidence, and dividing the conflicts into the uncertain part before processing.

According to the above analysis of the two solutions of evidence modification and the improved combination principle, although improved combination principle can eliminate conflicts when conflicts occur, it also loses some excellent properties of the combination rule itself due to the modification of the Dempster's combination rule. This will make the computational complexity of data fusion process relatively high, in especial if number of evidence sources and focus elements of the frame of discernment are large, as well as may even be impossible to calculate [26].

In the study, we conduct evidence conflict from the perspective of evidence itself modification. At the same time, an improved combination approach for conflicting evidence is proposed. In process of correcting original evidence, the evidence is first measured by measuring the evidence distance and evidence conflict, and then the weight of each evidence is determined according to the size of the difference. Then, the weighting coefficient is taken as a discounting factor, and the original evidence is discounted by the discounting operation. In the process of discounting, the assignment of basic belief is modified according to the discounting factor and the belief degree is redistributed. Finally, Dempster's combination rule was applied to combine the modified evidence.

The rest of the paper is made below: Section 2 introduces the foundations of evidence theory. In addition, the weighted evidence combination method is proposed in Section 3. Numerical instances are provided in Section 4 to illustrate the effectiveness of suggested approach. Finally, the conclusions are given in section 5.

2 Preliminary Work

This part mainly introduces the foundational concepts commonly used in evidence theory. The most commonly applied distance measurement between the evidence is also shown below.

2.1 Basics of Evidence Theory

In the evidence or Demater-Shafer theory, propositions are usually expressed as corresponding sets. Let $\Omega = \{w_1, w_2, \cdots, w_i, \cdots, w_n\}$ be a finite complete group with two reciprocal repulsive elements, as well as Ω is the frame of discernment of the problem studied. The frame of discernment contains all the possible answers to be conceived to the question at hand, and any proposition corresponds to a subset of the set Ω.

Considering n factors exist in the set Ω, the set of propositions consisting all subsets of Ω are known as power set of Ω, written 2^Ω that contains 2^Ω propositions. For instance, assume that the frame of discernment $\Omega = \{w_1, w_2, w_3\}$, then the set of proposition $2^\Omega = \{\phi, \{w_1\}, \cdots, \{w_n\}, \{w_1, w_2\}, \cdots, \Omega\}$, where factor ϕ stands for an empty group. This framework can be the most fundamental concept in mathematical evidence theory, and there are three basic functions defined on the frame of discernment: mass function, belief function, as well as plausibility function.

Assuming that Ω is the frame of discernment of the problem studied, if there is a mapping function $m: 2^\Omega \to [0,1]$ on 2^Ω to [0,1], and the following conditions are satisfied:

$$\begin{cases} \sum_{A \in 2^\Omega} m(A) = 1 \\ m(\phi) = 0 \end{cases}. \quad \textbf{(1)}$$

where m represents the mass function on Ω, as well as is also realized as basal belief assignment (BBA).

As for $A \in 2^\Omega$, $m(A)$ represents the belief value of the suggestion A, which shows degree of support that suggestion A is proofed by the evidence. When $m(A) > 0$, then proposition A is called a focal element. It is important to note that $m(A)$only represents the belief value of the proposition A, however does not contain belief value of its subset $B \subset A$. Especially, as for full set Ω, $m(\Omega)$ stands for degree of unknown, thus evidence theory can make an effective distinction between the conceptions of "indeterminacy" and "unknown". Moreover, ϕ could not be a focal element. due to the fact that the Shafer model is a Closed-World Assumption, considering elements included in the identification framework to be reciprocally excluding and complete.

Assume Ω is the frame of discernment of question under research, and m can be the mass function defined on Ω, if the function Bel is defined as:

$$Bel(A) = \sum_{B \subset A} m(B),\ \forall A \subseteq \Omega \quad \textbf{(2)}$$

then Bel is known as the belief function on Ω. For any $A \subseteq \Omega$, $Bel(A)$ is known as the confidence level of the proposition A, and reflecting the lower limit on the degree of support of the evidence for the proposition A.

Assume Ω is the frame of discernment of question under research, and m can be the mass function defined on Ω, if the function Pl is defined as:

$$Pl(A) = \sum_{A \cap B \neq \phi} m(B),\ \forall A \subseteq \Omega \quad \textbf{(3)}$$

then Pl is known as the plausibility function on Ω. For any $A \subseteq \Omega$, $Pl(A)$ is known as the plausibility of the proposition A, and represents the degree of non-opposition of the evidence to the proposition A, reflecting the upper limit on the degree of supporting of the evidence of suggestion A. Interval $[Bel(A), Pl(A)]$ is known as the uncertain belief interval of the proposition A, which represents the value range of the degree of uncertainty that occurs for the proposition A.

In practical applications, decision makers generally collect the evidence for the problem concerned from many origins (e.g. sensor observations, expert assessments, etc.), and how to combine the evidence for decision making is the key to the problem of uncertain reasoning. In frame of evidence principle, conventional Dempster's combination principle is applied to generate fusion consequences of the evidence. Dampster's rule is currently the most commonly used combination method due to its computational simplicity and good mathematical properties.

Let m_1 and m_2 are two mass functions with independence on identification framework Ω, for $\forall A, B, C \subseteq 2^{\Omega}$, the principle of Dempster's combination can be expressed below:

$$m_{\oplus}(A) = m_1(B) \oplus m_2(C) = \begin{cases} 0, & B \cap C = \phi \\ \frac{\sum_{B \cap C = A, \forall B, C \subseteq \Omega} m_1(B) \times m_2(C)}{1-k}, & B \cap C \neq \phi' \end{cases} \quad (4)$$

where $k = \sum_{B \cap C = \phi, \forall B, C \subseteq \Omega} m_1(B) \times m_2(C)$ describes the entire conflict between m_1 and m_2, and all focal elements are proportionally redistributed through a standard procedure.

2.2 Evidence Distance

In [27], Jousselme et al. proposed a famous distance, denoted as d_J. The distance treats the body of evidence as a multidimensional vector. The conflict between two pieces of evidence is quantified in terms of the distance among different vectors. Let m_1 and m_2 be the evidence gathered by two distinct sensors on identification framework Ω. The distance d_J among m_1 and m_2 has formal definition below:

$$d_J(m_1, m_2) = \sqrt{\frac{1}{2}(m_1 - m_2)^T D (m_1 - m_2)} \quad (5)$$

where D represents a $2^{|\Omega|} \times 2^{|\Omega|}$ matrix, and the factors in D can be calculated as: $D_{ij} = \frac{|A_i \cap B_j|}{|A_i \cup B_j|}, A_i, B_j \in 2^{\Omega}$

The method of measuring distance is widely used in various scenarios where there is conflicting evidence. However, in certain unique situations, it cannot be enough to reveal major distinctions between two BBAs, as well as computational complex rate of the measure grows quickly as the matrix D grows.

3 The Weighted Combination Method

A weighted combining approach for conflicting evidence of multisensor data fusion is suggested in the study. This combination approach is based on evidence discounting approach, as well as the acquisition of discounting (weighting) factor can be key of this method. The combination approach has the definition of different measures involving evidence distance as well as evidence conflict to describe distinctions between two pieces of evidence, and to obtain reliability of each evidence source on the assuming that most of evidence sources are reliable. According to relationship among credibility and weight, credibility is normalized into a weighting factor and discounted.

3.1 Evidence Discounting Algorithm

A new evidence discounting algorithm is presented in the section. Credibility of different evidence sources can be evaluated with difference between the evidence sources and the average level. On this basis, evidence is discounted to achieve the focus of evidence and make each piece of evidence closer to the overall estimate level. The specific process of this discounting algorithm is as follows:

(1) The mean value $\overline{m(A_j)}$ of the degree of support by each evidence source is calculated for every focal element in identification framework. It is considered that the whole evidence fusion system is highly reliable, that is, most of the sources of evidence are reliable and accurate. Therefore, the calculated average of the degree of support of each focal element also reflects the overall level of trustworthiness of that focal element. This value can represent the average level of trustworthiness of that focal element, and the higher its average level of trustworthiness, the higher the probability that the final decision will be for that focal element. The average confidence values of all focus elements obtained are shown in equation (6).

$$\overline{m(A_j)} = \frac{1}{N} \sum_{i=1 \cdots n} m_i(A_j) \quad (6)$$

(2) The dissimilarity measure $DismP(m_i, \overline{m})$ among every of evidence m_i and mean BBA $\overline{m}$ is calculated. Although the evidence distance d_J can effectively describe the difference between the evidence as a whole, it cannot represent the inconsistency between their main focal elements. The inconsistency between main focal elements can be measured by the conflict between the evidence. If two BBAs are reciprocally conflicting, singletons with maximal probability ought to be opposite and inconsistent. Based on the thought, the probability-based conflict measurement can be composed of:

$$BetP(w) = \sum_{w \in A, A \subseteq \Omega} \frac{1}{|A|} m(A), \quad (7)$$

$$ConfP(m_1, m_2) = \begin{cases} 0, & if \ \underset{x \in \Omega}{\operatorname{argmax}} BetP_{m_1}(x) \cap \underset{x \in \Omega}{\operatorname{argmax}} BetP_{m_2}(x) \neq \phi \\ \frac{1}{2} \sum_{x \in X} |BetP_{m_1}(x) - BetP_{m_2}(x)|, & otherwise. \end{cases} \quad (8)$$

where $X = \{\underset{x \in \Omega}{\operatorname{argmax}} P_{m_1}(x), \underset{x \in \Omega}{\operatorname{argmax}} P_{m_2}(x)\}$,

We define the dissimilarity measure $DismP(m_i, \overline{m})$ between the mass function m_i and $\overline{m}$ by:

$$DismP(m_i, \overline{m}) = ConfP(m_i, \overline{m}) d_J(m_i, \overline{m}) \quad (9)$$

(3) The credibility degree of every evidence Cre_i is calculated based on degree of dissimilarity of each evidence source. In the selection of the calculation formula, first, the degree of dissimilarity and the level of trust should satisfy the negative correlation. Namely, when dissimilarity degree of evidence source is higher the trust level is lower. When dissimilarity degree of evidence source can be lower, the trust level is higher. In addition, the calculated trust level also needs to be satisfied, when degree of dissimilarity is small, the trust level is very high. When the degree of dissimilarity is approximately zero, that is, roughly accurate, confidence in the source of evidence should be close to infinite. When the degree of dissimilarity increases, the trust level should drop rapidly; when the degree of dissimilarity is very large, the trust

level is close to 0, which is basically distrust. Therefore, the inverse proportional function is chosen here as the conversion function between the dissimilarity level and the trust level, and the credibility degree of evidence can be defined below:

$$Cre_i = \frac{1}{DismP(m_i,\overline{m})} \tag{10}$$

(4) Considering the credibility degree as the reliability of evidence, weight coefficient of each evidence can be calculated through normalizing reliability. In the discounting operation, each piece of evidence should have a discounting (weighting) factor between 0 to1. Therefore the weighting factor $\alpha_i$of the evidence m_i is denoted as below:

$$\alpha_i = \frac{Cre_i}{max\{Cre_i\}} \tag{11}$$

(5) Using the weighting factors obtained from equation (11), the evidence is discounted from the original evidence by the discounting method. This method assumes that the original evidence is not fully reliable and a coefficient should be decided to discount evidence based on the facts, as well as this weighting coefficient is called the discounting factor.

The choice of discounting factor is usually determined by the dissimilarity between different pieces of evidence. The evidence that has a greater conflict with other evidence requires a smaller discounting factor, while the evidence that has a smaller conflict can be assigned a larger discounting factor. After the discount, the mass of the original evidence with low reliability is discounted, and the discounted mass is allocated to the unknown part. The specific equation of the discounting method is shown as below:

$$\begin{cases} m_i^{\alpha}(A) = \alpha \times m_i(A) \\ m_i^{\alpha}(\Omega) = \alpha \times m_i(\Omega) + (1-\alpha) \end{cases} \tag{12}$$

According to equation (12), the degree of dissimilarity that each evidence source contains have been extracted and put into the unknown part $m(\Omega)$. According to the description of mass function, the belief value of unknown part is not available for decision making, and now it is also necessary to redistribute the obtained belief value of unknown part to facilitate decision making and eliminate the influence of conflicts on the fusion results.

According to equation (7), the unknown mass of belief $m_i^{\alpha}(\Omega)$ obtained after discounting is redistributed with the probability conversion function, and the final mass distribution of each focal element is defined as:

$$m_i'(A) = m_i^{\alpha}(A) + \sum_{A\in B,B\subseteq\Omega}\frac{m(B)}{|B|} \tag{13}$$

The result of equation (13) is the discounted mass assignment, which will be used in the subsequent process for data fusion. To make the above discounting algorithm clearer, the detailed flow of this algorithm is shown in Table 1, where the input is the original evidence and the output is the discounted evidence.

Table 1. Evidence discounting algorithm based on Shafer's discounting method

Algorithm: Shafer's discounting method-based evidence discounting algorithm

Input: Original evidence m_i
Output: Evidence after discounting m_i'
1: **for** j **in** the frame of discernment $\Omega = \{w_1,\cdots,w_n\}$
2: Calculate the mean value $\overline{m(A_j)}$
3: **end**
4: **for** i **in** list of evidence sources $\{m_1, m_2, \dots, m_N\}$
6: Compute the measure of conflict $ConfP(m_i,\overline{m})$
7: Calculate the dissimilarity $DismP(m_i,\overline{m})$
8: **end**
9: Calculate the credibility degree Cre_i
10: Discounting according to Shafer's method to obtain the corrected data $m_i^{\alpha}(A)$ and the unknown part $m_i^{\alpha}(\Omega)$
15: Redistribution of $m_i^{\alpha}(\Omega)$ confidence according to equation (13)
16: **Back to** Evidence after discounting m_i'

3.2 Fusion of Dempster's Combination Method

The iterative fusion is applied in procedure of data fusion using Dempster's integration principle to solve issue of large computational complexity of high-dimensional evidence. That is, the mathematical properties of the exchange and combination laws of the Dempster's rule are used to perform iterative computation of the evidence to be fused. In this section, the conclusion that fusion consequences of N pieces of evidence can be independent of fusion order and that two pieces of evidence can be selected for iterative fusion at a time will be proved based on this property.

To prove the above conclusion, the fusion results after exchanging the order of two pieces of evidence are not directly calculated here. Instead, we first calculate the fusion consequences of N pieces of evidence as well as further prove that fusion consequences are independent of order of calculation. In calculating the fusion results of N pieces of evidence, mathematical induction approach is applied to calculate them. Fusion result between any two pieces of evidence is calculated first. The ith evidence is chosen to be fused with the jth evidence, and the result obtained is shown in equation (14).

$$\begin{aligned} m_{i,j}(A_1) &= \frac{1}{k}\left[m_i(A_1)m_j(A_1) + m_i(A_1)m_j(\Omega) + m_i(\Omega)m_j(A_1)\right] = \frac{1}{k}\left[\frac{m_{i,1}}{1-m_{i,1}}m_i(\Omega)\frac{m_{j,1}}{1-m_{j,1}}m_j(\Omega) + \frac{m_{i,1}}{1-m_{i,1}}m_i(\Omega)m_j(\Omega) + \frac{m_{j,1}}{1-m_{j,1}}m_i(\Omega)m_j(\Omega)\right] = \\ &\frac{1}{k}\left[\frac{m_{i,1}}{1-m_{i,1}}\frac{m_{j,1}}{1-m_{j,1}} + \frac{m_{i,1}}{1-m_{i,1}} + \frac{m_{j,1}}{1-m_{j,1}}\right]m_i(\Omega)m_j(\Omega) = \frac{1}{k}\left[\frac{1}{(1-m_{i,1})(1-m_{j,1})} - 1\right]m_i(\Omega)m_j(\Omega) \end{aligned} \tag{14}$$

After the results of data fusion between two pieces of evidence are obtained, the fusion results to be calculated can be assumed by mathematical induction. It can be seen from equation (14) that in the equation for the two evidence i and j, in the final fusion result, the factors related to i and j are multiplied, and the two parts of the factors in the equation are completely symmetric. Therefore, the fusion results between N pieces of evidence can be summarized as equation (15).

$$m_k(A_1) = \frac{1}{k}\left[\frac{1}{(1-m_{1,1})(1-m_{2,1})\cdots(1-m_{N,1})}\right] \times m_1(\Omega)m_2(\Omega)\cdots m_N(\Omega) = \frac{1}{k}\left[\frac{1}{\prod_{i=1}^{N}(1-m_{i,1})} - 1\right] \times \prod_{i=1}^{N} m_i(\Omega) \quad \textbf{(15)}$$

From the fusion results of N pieces of evidence using equation (15), it can be seen that after each fusion, for the ith evidence, factorization associated with the order i of evidence includes following two multiplication equations (16) and equations (17).

$$\frac{1}{\prod_{i=1}^{N}(1-m_{i,1})} \quad \textbf{(16)}$$

$$\prod_{i=1}^{N} m_i(\Omega) \quad \textbf{(17)}$$

As can be seen from the above two factor decomposition, each factor decomposition is obtained by multiplying N symmetric factors, and each factor is only related to the confidence of the ith evidence source. From the exchange law of multiplication, we know that for several equations multiplied together, changing the order of operations does not impact eventual consequence of operation. Therefore, iterative fusion approach can be used. In addition, with the use of the iterative fusion approach, the problem of high computational complex rate of Dempster's combination principle is well solved.

Specific iterative process of this iterative fusion approach is shown in Table 2 below. The input of this algorithm is a matrix of $M \times N$, which represents the discounted evidence, where M represents number of evidence and N represents number of focal elements on identification framework. Each row of matrix is degree of support given by evidence for each focal element. The output result n indicates that the final result is the nth focal element on identification framework.

Table 2. Dempster's iterative integration algorithm

Algorithm: Dempster's iterative combination
Input: $M \times N$ dimensional array Arr
Output: Combined result n
Select the first evidence to $Arr[0]$ participate in the fusion
for $i = 1{:}M$
Evidence $Arr[i]$ involved in integration
Calculate the conflicting factor for this round of fusion k
Calculate the fusion result of this round $temp$
if $i = M - 1$
Iterative Fusion Results $ans = temp$
else
$temp$ participate in the next fusion
end
end
$max = 0, n = 0$
for max **in** ans
if $mass > max$
$max = mass, n = i + 1$
Return to n

In Table 2, the algorithmic process of Dempster's combination using iterative approach is given. For the corrected evidence, eventual consequence is obtained after iterative fusion and decision process.

4 Experiment Results and Analysis

In the part, we conduct two experiments to prove the validity of our combined method, which brings in a novel method to decide weight of evidence. We supposed that data gathered from the sensor had been processed into BBAs via certain existing algorithm. The first experiment was applied to verify the ability to handle conflicts, and the second experiment was used to determine fast convergence of algorithm, where the sources of evidence were provided by different sensor nodes.

4.1 Comparison of The Fusion of Conflicting Evidence

This section will simulate and analyze the conflict handling capability of the proposed method. In procedure of information fusion using D-S evidence principle, the main element impacting final fusion consequence is conflict of evidence, as well as the optimization of evidence theory is mainly aimed at its conflict processing. In this experiment, several commonly used evidence theory optimization approaches will be used to combine the basic probability distribution of each sensor reading with large conflicts.

Methods used in the experiment include Dempster's combination rule, Yager's combination approach [28], Murphy's combination approach [29], Sun's combination approach [30] and the method suggested in the study. Suppose that in the target recognition system, all five sensor nodes take part in the target observation, that is, S_1, S_2, S_3, S_4, S_5. After local recognition and judgment of the observation data of the same target, five pieces of evidence are uploaded to the fusion center for global fusion. Meanwhile, there may be three distinct categories of monitoring targets, so identification framework of the instance is represented as $\Omega = \{A, B, C\}$. Assume the real target is sensed by five sensors, and the sensor reports received from these sensors are modeled as BBAs, represented in Table 3 as m_1, m_2, m_3, m_4, m_5.

Table 3. BBAs of sensor information in target recognition system

	A	B	C
m_1	0.5	0.3	0.2
m_2	0	0.9	0.1
m_3	0.6	0.1	0.3
m_4	0.5	0.1	0.4
m_5	0.5	0.2	0.3

As can be seen from the five BBAS, only S_2 thinks that the monitoring target belongs to class B rather than class A. The other four sensors considered that the monitoring target was most likely to belong to class A, and less likely to belong to class B and C. It may be due to the sensor S_2 interfered by circumstances, which not only results in great conflicts among observation data reported by S_2 and that provided by the other four sensors, but also leads to its wrong decision.

The fusion results are indicated in Table 4. The data in the table are the mass assignments of the single focal elements and the mass assignments of the unknown parts after fusion.

Table 4. Fusion consequences with distinct combination method

Combination methods	A	B	C	Ω
Dempster's method	0	0.4	0.6	0
Yager's method	0	0.0004	0.0005	0.9991
Murphy's method	0.7045	0.1954	0.1001	0
Sun's method	0.2166	0.1748	0.1656	0.4480
Proposed Method	0.8737	0.0237	0.1026	0

As can be seen from aforementioned table, for the reliability of the results, Yager's approach and Sun's method retain a large unknown information value Ω. For the sake of decreasing indeterminacy of fusion consequences, the probability function $BetP(\Omega)$ should be used to divide unknown information Ω into each focal element during decision-making. The mass distribution of each focal element after belief redistribution is indicated in Figure 1.

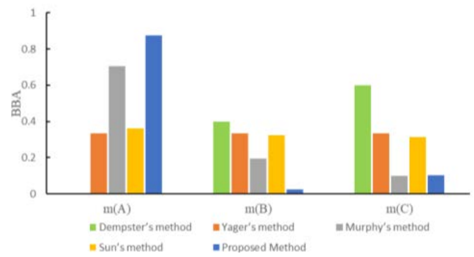

Figure 1. Fusion results of conflicting data after belief redistribution

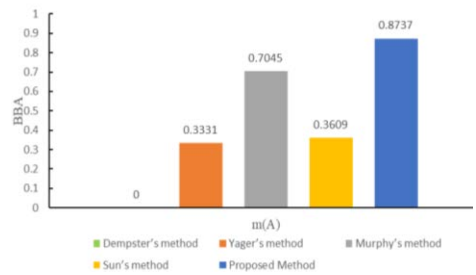

Figure 2. Fusion results for target A

It can be seen from Figure 1 that the forms of fusion results are different in the above five combination methods. For Dempster's combination method, when the belief value of the focal element is 0, the value of that focal element after fusion is always 0, indicating that the method has poor ability to deal with conflicting data. Although the Yager's method can process conflicting data, it takes the conflicting part completely as the unknown part Ω, making the available mass distribution relatively small, and the difference of the belief value of each focal element in the final result is very small, resulting in the fusion result basically losing the decision-making ability. Although the Sun's combination method resolves the conflict to a certain extent, due to the retention of a large value of unknown information Ω, resulting in little difference in the mass assignments of individual focal elements and weaker decision-making ability. Murphy's average weighting method is a way to average the weighting of the evidence, and it can be seen from the fusion results that it has a higher degree of support for the true focal element A, indicating a better conflict handling ability, but this method considers all evidence sources to be balanced, which is not consistent with the variability among the sensor reports in the actual situation. In contrast, the proposed method has best fusion consequences compared with other fusion methods, without leaving the unknown information of conflicting Ω, and also has a high degree of support for real focal element with good performance in decision making and fusion accuracy. As can be seen from Figure 2, the fusion results of the method in this paper are more supportive of the real target A than those of other methods. These results suggest that our proposed approach is a more effective resolution to the conflicting problem.

4.2 Analysis of Convergence Capacity

In this subsection, the convergence ability of the proposed method will be simulated and analyzed. The comparison method selected is Dempster's combination principle as well as Yager's method. In the fusion process, the sensor report based on BBA model will seriously affect the accuracy of the final result, especially when the error report is given. Therefore, the fusion algorithm needs to have a good convergence ability to be able to correct the results based on the data from other evidence when the data from one piece of evidence is abnormal, as well as number of sources of evidence required to reach convergence should be as small as possible. Assume that three kinds of faults for the machines of the fault diagnosis problem exist, which makes up of identification framework $\Omega = \{F_1, F_2, F_3\}$. The group of sensors showed by $S = \{S_1, S_2, S_3, S_4, S_5\}$ are distributed in distinct positions to gather fault data. Mass function is used to model fault data as BBAs. m_1, m_2, m_3, m_4 and m_5 represents the BBAs of the five sensors S_1, S_2, S_3, S_4 as well as S_5 in Table 5.

Table 5. The BBAs of sensor data in fault diagnosis problem

	F_1	F_2	F_3
m_1	0.6	0.2	0.2
m_2	0	0.7	0.3
m_3	0.5	0.3	0.2
m_4	0.4	0.3	0.3
m_5	0.5	0.1	0.4

In Table 5, we can note that m_1, m_3, m_4 and m_5 strongly sustain fault type F_1, while m_2 provides the biggest belief value to fault type F_2. It is obvious that m_2 is an abnormal evidence. In this experiment, m_1 and m_2 are selected for combination in the beginning. Subsequently, the other pieces of evidence are added for fusion in order until all BBAs are involved in fusion. As number of the sources of evidence grows, variation curve of belief values to the real fault type F_1 of the final fusion consequence is indicated in Figure 2. Where, vertical coordinate is belief value in actual fault type F_1.

From Figure 3, it is showed that if a piece of evidence with belief value of 0 to the fault type F_1 is added, the fusion result of Dempster's combination principle comes to a wrong results which also assign belief value of 0 to F_1. As the number of BBAs increases, the fusion results for the belief value of the fault type F_1 remains 0. It is clear that Dempster's combined principles cannot deal with conflict. By contrast, if using the method presented in this paper and Yager's method, the belief degree drops sharply when a piece of evidence with the belief value of 0 is added, but it does not result in 0. At the same time, the conflict is processed and calculated according to the existing two BBAs. As the number of BBAs continues to increase, the belief value for F_1 of the fault type continues to increase. Even with only three BBAs, the belief value assigned to F_1 by the method in this paper exceeds 0.5. In addition, the method presented in this paper has the highest belief value of 73.32% for fault type F_1 , as shown in Figure 4. It is indicated that algorithm has a strong correction ability when one sensor gives a wrong BBA, and can make the combined results converge quickly on the basis of other normal BBAs.

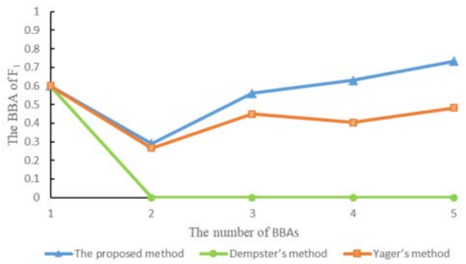

Figure 3. The comparison of the belief value for F_1

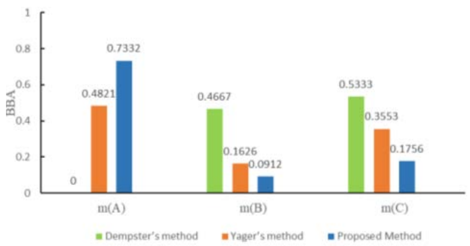

Figure 4. The comparison of fusion results

5 Conclusion

In this paper, a weighted evidence combined method is proposed to solve the problem of conflicting evidence in multisensor data fusion. Shafer's discount method is used to correct the original evidence, in which the most critical discount factor is defined according to the distance measure and conflict measure between each piece of evidence and the average BBA. Then, the Dempster's combination rule is utilized to realize fast fusion of multisensor reports through iterative fusion. Experimental consequences indicate that this way can efficiently solve conflict evidence fusion problem, and the fusion effect is better than other related methods. In addition, the method has strong convergence ability as well as can quickly correct errors when the report of a sensor is abnormal. In future work, we intend to discover more reasonable estimators of sensor weights and design more efficient combinatorial approaches to deal with uncertain as well as conflicting data.

References

[1] Y. Zhang, Y. Liu, Z. Zhang, H.-C. Chao, J. Zhang, Q. Liu, A weighted evidence combination approach for target identification in wireless sensor networks, *IEEE Access*, Vol. 5, pp. 21585-21596, October, 2017.

[2] Z.-G. Liu, Y. Liu, J. Dezert, F. Cuzzolin, Evidence combination based on credal belief redistribution for pattern classification, *IEEE Transactions on Fuzzy Systems*, Vol. 28, No. 4, pp. 618-631, April, 2020.

[3] X. Wang, Y. Song, Uncertainty measure in evidence theory with its applications, *Applied Intelligence*, Vol. 48, No. 7, pp. 1672-1688, July, 2018.

[4] C. Qiang, Y. Deng, A new correlation coefficient of mass function in evidence theory and its application in fault diagnosis, *Applied Intelligence*, Vol. 52, No. 7, pp. 7832-7842, May, 2022.

[5] P. Sureeyatanapas, N. Waleekhajornlert, S. Arunyanart, T. Niyamosoth, Resilient supplier selection in electronic components procurement: an integration of evidence theory and rule-based transformation into TOPSIS to tackle uncertain and incomplete information, *Symmetry*, Vol. 12, No. 7, Article No. 1109, July, 2020.

[6] Z. Zhang, C. Jiang, Evidence-theory-based structural reliability analysis with epistemic uncertainty: a review, *Structural and Multidisciplinary Optimization*, Vol. 63, No. 6, pp. 2935-2953, June, 2021.

[7] Y. Zhang, Y. Liu, Z. Zhang, N. Zhao, Collaborative fusion for distributed target classification using evidence theory in IoT environment, *IEEE Access*, Vol. 6, pp. 62314-62323, October, 2018.

[8] C. Zhu, B. Qin, F. Xiao, Z. Cao, H. M. Pandey, A fuzzy preference-based Dempster-Shafer evidence theory for decision fusion, *Information Sciences*, Vol. 570, pp. 306-322, September, 2021.

[9] X. Cheng, J. Zhou, X. Zhao, Safety assessment of vehicle behaviour based on the improved D–S evidence theory, *IET Intelligent Transport Systems*, Vol. 14, No. 11, pp. 1396-1402, November, 2020.

[10] F. Xiao, Multi-sensor data fusion based on the belief divergence measure of evidences and the belief entropy, *Information Fusion*, Vol. 46, pp. 23-32, March, 2019.

[11] A. Stief, J. R. Ottewill, J. Baranowski, M. Orkisz, A PCA and two-stage Bayesian sensor fusion approach for diagnosing electrical and mechanical faults in induction motors, *IEEE Transactions on Industrial Electronics*, Vol. 66, No. 12, pp. 9510-9520, December, 2019.

[12] Y. Xue, Y. Deng, Decision making under measure-based granular uncertainty with intuitionistic fuzzy sets, *Applied Intelligence*, Vol. 51, No. 8, pp. 6224-6233, August, 2021.

[13] P. Liu, H. Yang, Three-way decisions with intuitionistic uncertain linguistic decision-theoretic rough sets based on generalized Maclaurin symmetric mean operators, *International Journal of Fuzzy Systems*, Vol. 22, No. 2, pp. 653-667, March, 2020.

[14] Y. Deng, Uncertainty measure in evidence theory, *Science China Information Sciences*, Vol. 63, No. 11, pp. 1-19, November, 2020.

[15] C. Fu, Q. Zhan, W. Liu, Evidential reasoning based ensemble classifier for uncertain imbalanced data, *Information Sciences*, Vol. 578, pp. 378-400, November, 2021.

[16] D. Qiao, K.-W. Shen, J.-Q. Wang, T.-L. Wang, Multi-criteria PROMETHEE method based on possibility degree with Z-numbers under uncertain linguistic environment, *Journal of Ambient Intelligence and humanized computing*, Vol. 11, No. 5, pp. 2187-2201, May, 2020.

[17] Y. Tian, X. Mi, L. Liu, B. Kang, A new soft likelihood function based on d numbers in handling uncertain information, *International Journal of Fuzzy Systems*, Vol. 22, No. 7, pp. 2333-2349, October, 2020.

[18] J. Wang, Y. Mao, Z. Li, J. Gao, H. Liu, Robust fusion estimation for multisensor uncertain systems with state delay based on data-driven communication strategy, *IEEE Access*, Vol. 8, pp. 151888-151897, August, 2020.

[19] D. Zhu, X. Cheng, L. Yang, Y. Chen, S. X. Yang, Information Fusion Fault Diagnosis Method for Deep-Sea Human Occupied Vehicle Thruster Based on Deep Belief Network, *IEEE Transactions on Cybernetics*, pp. 1-14, March, 2021.

[20] K. K. Sharma, A. Seal, Modeling uncertain data using Monte Carlo integration method for clustering, *Expert systems with applications*, Vol. 137, pp. 100-116, December, 2019.

[21] A. P. Dempster, Upper and Lower Probabilities Induced by a Multivalued Mapping, *Annals of Mathematical Statistics*, Vol. 38, No. 2, pp. 325-339, April, 1967.

[22] G. Shafer, *A mathematical theory of evidence*, Princeton university press, 1976.

[23] F. Xiao, B. Qin, A weighted combination method for conflicting evidence in multi-sensor data fusion, *Sensors*, Vol. 18, No. 5, Article No. 1487, May, 2018.

[24] Z. Deng, J. Wang, A novel evidence conflict measurement for multi-sensor data fusion based on the evidence distance and evidence angle, *Sensors,* Vol. 20, No. 2, Article No. 381, January, 2020.

[25] Z. Lin, J. Xie, Research on improved evidence theory based on multi-sensor information fusion, *Scientific Reports*, Vol. 11, No. 1, pp. 1-6, April, 2021.

[26] W. Zhang, Y. Deng, Combining conflicting evidence using the DEMATEL method, *Soft computing*, Vol. 23, No. 17, pp. 8207-8216, September, 2019.

[27] A.-L. Jousselme, D. Grenier, É. Bossé, A new distance between two bodies of evidence, *Information fusion*, Vol. 2, No. 2, pp. 91-101, June, 2001.

[28] R. Yager, On the Dempster-Shafer framework and new combination rules, *Information sciences*, Vol. 41, No. 2, pp. 93-137, March, 1987.

[29] C. K. Murphy, Combining belief functions when evidence conflicts, *Decision Support Systems*, Vol. 29, No. 1, pp. 1-9, July, 2000.

[30] Q. Sun, X. Ye, W. Gu, A New Combination Rules of Evidence Theory, *Acta Electronica Sinica*, Vol. 28, No. 8, pp. 117-119, August, 2000

Biographies

Yin Liu, currently a Ph.D. student in the college of Engineering at Peking University. His research areas include Intelligent Biomimetic Robot, Multi-Robot Systems and Control. He received his bachelor degree in University of Warwick and master degree in University of Birmingham both in UK.

Yang Zhang received his Ph.D degree in the School of Electronics and Information Engineering from Beijing Jiaotong University in 2019. Currently, he is a teacher at Beijing Jiaotong University. His research fields include wireless sensor network techniques, and wearable sensor network techniques, including data fusion, pattern recognition, risk evaluation and decision making.