



Multi-sensor Data Fusion Based on Weighted Credibility Interval

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Abstract. The Dempster-Shafer combination rule often get wrong results when dealing with severely conflicting information. The existing typical improvement methods are mostly based on the similarity of attributes such as evidence distance, similarity and information entropy attribute as evidence weight correction evidence itself. Ultimately, the final weights of the evidences are applied to adjust the bodies of the evidences before using the Dempster's combination rule. The fusion results of these typical methods are not ideal for some complex conflict evidence. In this paper, we propose a new improved method of conflict evidence based on weighted credibility interval. The proposed method considers the credibility degree and the uncertainty measure of the evidences which respectively based on the Sum of Absolute Difference among the propositions and the credibility interval lengths. Then the original evidence is modified with the final weight before using the Dempster's combination rule. The numerical fusion example has verified that the proposed method is feasible and improved, in which the basic probability assignment (BPAs) to identify the correct target is 99.21% .

Keywords: Weighted credibility interval · Sum of absolute difference · Credibility interval length · Data fusion

1 Introduction

Dempster-Shafer evidence theory is an uncertainty reasoning method, which was firstly proposed by Dempster, and had been developed by Shafer. There are many advantages in Dempster's evidence theory. Firstly, a complete prior probability model is not required. After that, it can effectively deal with uncertain information, which is why it is widely applied in various fields [1, 2]. When combining highly conflicting evidence data, Dempster-Shafer evidence theory [3] often get counter-intuitive results. The improved method mainly divided into two categories, the first type is to revise the Dempster's combination rule, and the second type is to preprocess the body of evidence. The first kind of research work mainly includes Smets's method, Dubois and Prade's rule and Yager's combination rule [4]. However, the new combination rules tend to destroy the good mathematical properties of the original composition rules. More importantly, they cannot handle counter-intuitive error caused by sensor failure. Many researches tend

to preprocess the evidence that to solve the problem of highly contradictory evidence fusion.

The second kind of research work mainly considers the uncertainty measure and the credibility degree, which include Murphy's average method [5], Deng [6] proposed a method based on weighted average of the masses based on the evidence distance, Zhang's method [7], Yuan's method [8] based on vector space and the belief entropy. Xiao [9] proposed a multi-sensor fusion method combining belief divergence and Deng's entropy, which has a good effect. Most of these improvement methods only consider the similarity between evidences, and rarely consider the influence of evidences themselves. For complex evidence cases, there is still some room for improvement to the final fusion result.

In practical applications, when a sensor obtains information from a signal source, there is no uncertainty in the process of information generation and transmission. While in the aspect of information reception, with the reliability of the sensor, there is uncertainty in the information source obtained by different sensors.

In order to solve this problem, a new uncertainty parameter that is credibility interval lengths, is first proposed to measure the influence of proposition on final weight. Based on that, a new multi-sensor data fusion method is proposed. This method not only considers the credibility of the evidence, but also considers the influence of the uncertainty measure of the evidence on the weight. The credibility interval length of evidence interval $[Bel(A), Pl(A)]$ is used to represent the uncertainty degree of evidence itself. For each evidence, calculate the difference between the basic probability assignment and the proposition assignment under other evidence. Then the Sum of Absolute Difference indicates the support of other evidences, thus make a dent in the conflict degree between the evidences. We calculate two correction parameters based on the credibility interval lengths and the Sum of Absolute Difference among the propositions. Then the original evidence is modified with the final weight before using the Dempster's combination rule. The flow chart of the proposed method is shown in Fig. 1. To summarize, the primary contributions of this paper are listed as follows:

- (1) We propose a new uncertainty parameter, the length of the interval, to measure the impact of the proposition on the final weight. Based on this, a new multi-sensor data fusion method is proposed.
- (2) We validated the effectiveness of the proposed method in two real evidence cases and outperformed the existing excellent fusion methods.

The rest of this paper is organized as follows. In Sect. 2, the theoretical basis and improvement work of this paper are introduced, including a brief introduction to DS evidence theory and a new uncertainty parameter. Based on credibility interval lengths, an improved method for dealing with conflict evidence is proposed. The effectiveness of the proposed method is illustrated in Sect. 3 on two practical cases of target recognition and fault diagnosis. Finally, the conclusions and the next research work are given in Sect. 4.

2 Multi-sensor Data Fusion Based on Weighted Credibility Interval

2.1 Dempster-Shafer Evidence Theory

Dempster-Shafer evidence theory is an uncertainty reasoning method for dealing with uncertain problems. It is able to reason flexibly and has good effects even if there is no complete prior probability, or no knowledge of prior knowledge. And it is widely applied in dealing with uncertain problems. The basic model framework of Dempster-Shafer evidence theory is introduced in Fig. 1.

Definition 1 (Frame of discernment). In Dempster-Shafer evidence theory, a complete set of mutually exclusive events is defined as a frame of discernment which is described as $\Theta = \{\theta_1, \theta_2, \dots, \theta_n\}$. Where the set of all subsets in the identification framework is defined as 2^θ .

Definition 2 (Basic Probability Assignment Function). For a frame of discernment Θ , the basic probability assignment function is a mapping from 2^θ to $[0, 1]$, which satisfies the following condition, $m(\phi) = 0, \sum_{A \in \Theta} m(A) = 1$. The basic probability of any proposition A in the set 2^θ is assigned $m(A)$, indicating the support of the inference model to proposition A .

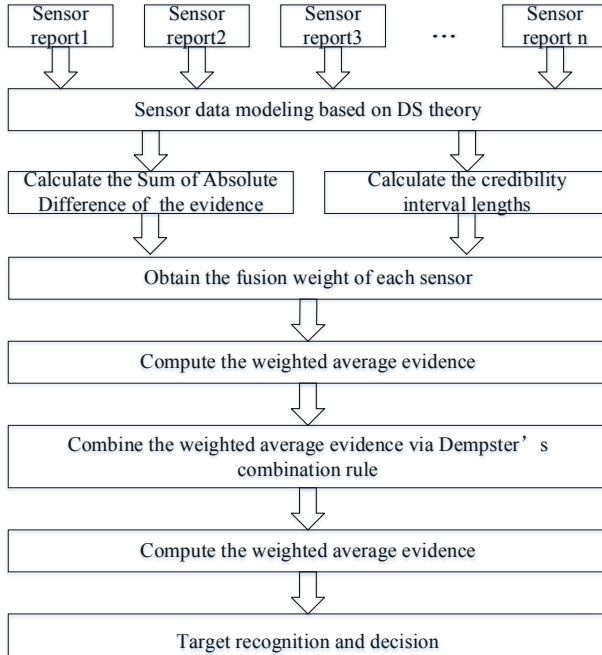


Fig. 1. The flow chart of the proposed method.

Definition 3 (Belief function). For the proposition A which $A \subseteq \theta$ in the recognition framework, the trust function $Bel: 2^\theta \rightarrow [0, 1]$, and is defined as,

$$Bel(A) = \sum_{B \subseteq A} m(B). \tag{1}$$

Where $Bel(A)$ is called the trust degree of proposition A , which indicates the overall credibility of proposition A in all evidences. Meanwhile, the plausibility function is defined as,

$$Pl(A) = 1 - Bel(\bar{A}) = \sum_{B \cap A \neq \emptyset} m(B). \tag{2}$$

Where $\bar{A} = \theta - A$. Obviously, $Pl(A)$ is greater than or equal to $Bel(A)$. The credibility interval consists of the belief function and the plausible function. And the relationship among them is shown in Fig. 2.

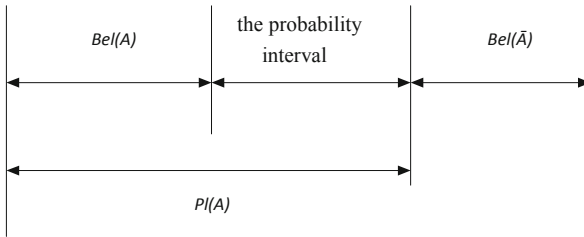


Fig. 2. Schematic diagram of the evidence interval.

Define interval $[Bel(A), Pl(A)]$ for the credibility interval, the interval is neither support the proposition A , nor refuse to it. But the credibility interval lengths reflects the relevance difference of proposition A and other propositions. When the length at 0, namely the $Bel(A) = Pl(A)$, evidence theory degenerates into the Bayes reasoning method. The average confidence interval length of each piece of evidence is used to represent the influence of the evidence on the weight.

Definition 4 (Dempster’s combination rule). Assuming m_1 and m_2 is two sets of basic probability assignment under the same recognition framework Θ , and the two sets of basic probability assignment are independent of each other, the combination rule is represented by symbols \oplus , and $m = m_1 \oplus m_2$, the specific definition is as follows.

$$m(A) = \begin{cases} 0 & A = \Phi \\ \frac{1}{1-k} \sum_{\cap A_i=A} \prod_{j=1}^n m_j(A_i) & A \neq \Phi \end{cases} \tag{3}$$

Where k is the conflict coefficient, which is defined as the formula (4).

$$k = \sum_{\cap A_i=\Phi} \prod_{j=1}^n m_j(A_i), 0 \leq k \leq 1. \tag{4}$$

2.2 Improved Method Based on Credibility Interval

Similar to the improvement ideas [5–7], the proposed method does not change the Dempster-Shafter combination rule, but focuses on solving the problem that the evidence theory cannot integrate the evidence of serious conflicts effectively. So the evidences of multiple sensors can be better applied to Dempster-Shafter combination rule. The improvement of the proposed method is to propose a weight based on credibility interval to represent the influence of the evidence itself on the final weight. And the propositional Sum of Absolute Difference of evidence is used to represent the similarity between evidence. The final weight is composed of these two modified parameters is used to preprocess the original evidence and weaken the degree of conflict between the evidences. For each body of evidence, we calculate the absolute difference between each proposition and other propositions, and measure the trust degree between evidences with the difference sum. On the other hand, we calculate the propositional credibility interval lengths of evidence. The longer the interval is, the more relevance different it is with other propositions, and the greater the weight is. For the convenience of assignment calculation, the complement set between the regions is used as the direct parameter. The reliability of the evidence itself is measured by the length of the average confidence interval. The final adjustment weight is obtained by modifying the two parameters, and then it is combined with the original evidence to obtain the weighted average evidence. Finally, the final fusion result is obtained by using the Dempster-Shafter evidence combination rule.

Under the frame of discernment Θ , $m_i(\cdot)$ ($1 \leq i \leq n$) is the basic probability assignment of the sensor i . The method based on weighted credibility interval is calculated as follows.

Step 1: The evidence interval matrix can be calculated by formula (5), and the range of evidence can be calculated by formula (6). The complement of credibility interval is used as the direct calculation parameter.

$$EIM_i = [Bel(\cdot), Pl(\cdot)]. \quad (5)$$

$$ROE_i(\cdot) = 1 - |Pl(\cdot) - Bel(\cdot)|. \quad (6)$$

Step 2: The Sum of Absolute Difference between each proposition and the others can be calculated by

$$Suad_i(A) = \sum_{A \subseteq 2^\theta, i \neq j} |m_i(A) - m_j(A)|. \quad (7)$$

Step 3: The average value of each row on two matrices ROE and $Suad$, which is denoted as two adjustment parameters.

$$\tilde{ROE}_i = \frac{ROE_i(\cdot)}{2^\theta}, 1 \leq i \leq n. \quad (8)$$

$$\tilde{Suad}_i = \frac{Suad_i(\cdot)}{2^\theta}, 1 \leq i \leq n. \quad (9)$$

Step 4: Support for evidence is expressed as Sup which is calculated by multiplying the two parameters obtained in step 3, then squaring, and taking the reciprocal.

$$Sup_i = \frac{1}{(\tilde{R}OE_i * \tilde{S}uad_i)^2}, 1 \leq i \leq n. \tag{10}$$

Step 5: The support of evidence is normalized as the final weight adjustment.

$$w_i = \tilde{S}up_i = \frac{Sup_i}{\sum_{s=1}^n Sup_s}, 1 \leq i \leq n. \tag{11}$$

Step 6: The weighted average evidence can be calculated by

$$m(\{.\}) = \sum m_i(\{.\}) * W_i \tag{12}$$

Step 7: The modified evidence is combined n-1 times by Dempster’s combination rule.

$$\tilde{m}(A) = \oplus_{i=1}^{n-1} (m_w). \tag{13}$$

Where, m_w is the weighted average evidence calculated in step 6.

3 Examples

In order to verify the improvement of the proposed method on the conflict evidence problem, experiments are carried out through MATLAB simulation, and the experimental results are compared and analyzed with the recent studies.

3.1 Example of Target Recognition

An evidence data from reference [6] is shown in Table 1. This is a multi-sensor based target recognition problem, an object set is defined as $\Theta = \{A, B, C\}$. The evidence information is independently collected by five different types of sensors, whose evidences are processed as basic probability assignments (BBAs).

Step 1: The evidence interval matrix can be calculated by formula (5), and the range of evidence can be calculated by formula (6).

$$EIM = \begin{pmatrix} [0.41, 0.41] & [0.29, 0.29] & [0.30, 0.30] & [0.71, 0.71] \\ [0.00, 0.00] & [0.90, 0.90] & [0.10, 0.10] & [0.10, 0.10] \\ [0.58, 0.93] & [0.07, 0.07] & [0.00, 0.35] & [0.93, 0.93] \\ [0.55, 0.90] & [0.10, 0.10] & [0.00, 0.35] & [0.90, 0.90] \\ [0.60, 0.90] & [0.10, 0.10] & [0.00, 0.35] & [0.90, 0.90] \end{pmatrix}$$

$$ROE = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 0.65 & 1 & 0.65 & 0.07 \\ 0.65 & 1 & 0.65 & 0.10 \\ 0.7 & 1 & 0.70 & 0.10 \end{bmatrix}$$

Table 1. The BBAs of a multi-sensor based target recognition.

BBAs	{A}	{B}	{C}	{A, C}
$S_1 : m_1(.)$	0.41	0.29	0.30	0.00
$S_2 : m_2(.)$	0.00	0.90	0.10	0.00
$S_3 : m_3(.)$	0.58	0.07	0.00	0.35
$S_4 : m_4(.)$	0.55	0.10	0.00	0.35
$S_5 : m_5(.)$	0.60	0.10	0.00	0.30

Step 2: The Sum of Absolute Difference between each proposition and others can be calculated by formula (7).

$$S_{uad} = \begin{bmatrix} 0.91 & 1.21 & 1.1 & 1 \\ 2.14 & 3.04 & 0.50 & 1 \\ 0.8 & 1.11 & 0.4 & 0.75 \\ 0.77 & 1.02 & 0.4 & 0.75 \\ 0.86 & 1.02 & 0.4 & 0.70 \end{bmatrix}$$

Step 3: The adjustment parameters are denoted as $\tilde{R}OE$ and $\tilde{S}uad$. It is equal to the average of the two rows of the matrix.

$$\tilde{R}OE_1 = 1; \tilde{R}OE_2 = 1; \tilde{R}OE_3 = 0.5925; \tilde{R}OE_4 = 0.6; \tilde{R}OE_5 = 0.625.$$

$$\tilde{S}uad_1 = 1.055; \tilde{S}uad_2 = 1.67; \tilde{S}uad_3 = 0.765; \tilde{S}uad_4 = 0.735; \tilde{S}uad_5 = 0.745.$$

Step 4: Support for evidence is expressed as Sup which is calculated by multiplying the two parameters obtained in step 3, then squaring, and taking the reciprocal.

$$Sup_1 = 0.8984; Sup_2 = 0.3586; Sup_3 = 4.8674; Sup_4 = 5.1419; Sup_5 = 4.6124;$$

Step 5: The support degree of evidence is normalized as the final weight adjustment.

$$\tilde{S}up_1 = 0.8984; \tilde{S}up_2 = 0.3586; \tilde{S}up_3 = 4.8674; \tilde{S}up_4 = 5.1419; \tilde{S}up_5 = 4.6124;$$

Step 6: The weighted average evidence can be calculated as follows.

$$\begin{aligned} m(\{A\}) &= 0.5534 \\ m(\{B\}) &= 0.1196 \\ m(\{C\}) &= 0.0192 \\ m(\{A, C\}) &= 0.3078 \end{aligned}$$

Step 7: The modified evidence is combined 4 times by Dempster's combination rule, and the results of target A is $m_f(\{A\}) = (((m \oplus m) \oplus m) \oplus m) (\{A\}) = 0.9023$. The same is available, $m_f(\{B\}) = 0.1201$, $m_f(\{A, C\}) = 0.0986$, The Combination results of different fusion algorithms on the evidence of target recognition shown in Table 2 and Fig. 3.

Table 2. Combination results of different fusion algorithms on the evidence of target recognition

Method	{A}	{B}	{C}	{A, C}	Target
Dempster [3]	0	0.1422	0.8578	0	C
Murphy [5]	0.9620	0.0210	0.0138	0.0032	A
Deng et al. [6]	0.9820	0.0039	0.0107	0.0034	A
Zhang et al. [7]	0.9886	0.0002	0.0072	0.0032	A
Yuan et al. [8]	0.9886	0.0002	0.0072	0.0039	A
Xiao [9]	0.9895	0.0002	0.0061	0.0043	A
Proposed method	0.9921	0.0001	0.0021	0.0058	A

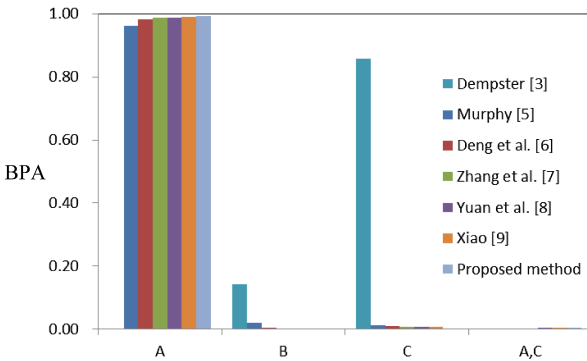


Fig. 3. The comparison of BBAs generated by different methods in Example 1.

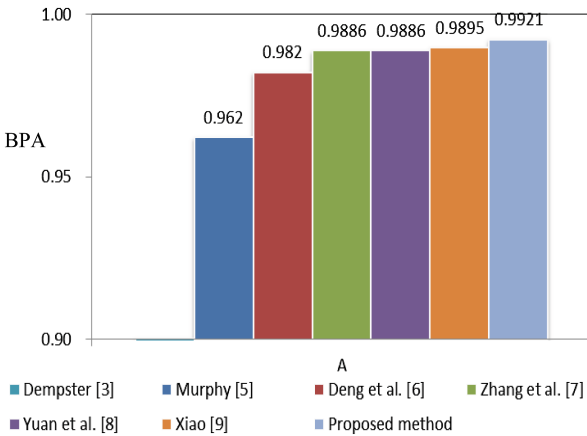


Fig. 4. Probability of target A being recognized

It can be seen that target *A* can be correctly identified in proposed method from Table 2 and Fig. 3. Dempster’s rule cannot deal with the conflict of evidence 2 and other evidence in this case, and reaches the wrong target *C*. While Murphy’s method [3], Deng et al.’s method [6], Zhang et al.’s method [7], Yuan et al. [8], Xiao [9] and the proposed method have certain effect on the processing of conflict evidence, identifying the correct target *A*.

As shown in Fig. 4, the proposed method present superior performance with a higher probability (99.21%) on target *A* compared with the best results in the comparison method. The numerical fusion example is verified that the proposed method is feasible and improved, of which weighted credibility interval can reduce the conflict of evidence.

3.2 Example of Fault Diagnosis

For the problem of fault diagnosis [10, 11], an evidence data from reference [10] as shown in Table 3. This is a multi-sensor based fault diagnosis problem, a object set is defined as $\Theta = \{F_1, F_2, F_3\}$. The evidence information is independently collected by three independently distributed sensors, whose evidence data are processed as basic probability assignments (BBAs).

Table 3. The BBAs of a multi-sensor based fault diagnosis.

BBAs	$\{F_1\}$	$\{F_2\}$	$\{F_2, F_3\}$	$\{F_1, F_2, F_3\}$
$S_1 : m_1(.)$	0.41	0.29	0.30	0.00
$S_2 : m_2(.)$	0.00	0.90	0.10	0.00
$S_3 : m_3(.)$	0.58	0.07	0.00	0.35

Step 1: The evidence interval matrix can be calculated by formula (5), and the range of evidence can be calculated by formula (6).

$$\begin{aligned}
 EIM &= \begin{pmatrix} [0.60, 0.80] & [0.10, 0.40] & [0.20, 0.40] & [1, 1] \\ [0.05, 0.15] & [0.80, 0.95] & [0.85, 0.95] & [1, 1] \\ [0.70, 0.80] & [0.10, 0.30] & [0.20, 0.30] & [1, 1] \end{pmatrix} \\
 ROE &= \begin{bmatrix} 0.80 & 0.70 & 0.80 & 1 \\ 0.90 & 0.85 & 0.90 & 1 \\ 0.90 & 0.80 & 0.90 & 1 \end{bmatrix}
 \end{aligned}$$

Step 2: The Sum of Absolute Difference between each proposition and others can be calculated by formula (7).

$$\text{Suad} = \begin{bmatrix} 0.65 & 0.70 & 0.05 & 0.20 \\ 1.20 & 1.40 & 0.10 & 0.10 \\ 0.75 & 0.70 & 0.05 & 0.10 \end{bmatrix}$$

Step 3: Two adjustment parameters which is denoted as \tilde{ROE} and \tilde{Suad} can be calculated. They are equivalent to the average values of two rows.

$$\tilde{ROE}_1 = 0.825; \tilde{ROE}_2 = 0.9125; \tilde{ROE}_3 = 0.9.$$

$$\tilde{Suad}_1 = 0.4; \tilde{Suad}_2 = 0.7; \tilde{Suad}_3 = 0.4.$$

Step 4: Support for evidence is expressed as Sup which is calculated by multiplying the two parameters obtained in step 3, then squaring, and taking the reciprocal.

$$Sup_1 = 0.4746; Sup_2 = 0.1267; Sup_3 = 0.3988;$$

Step 5: The support calculated in step 4 is used as the dynamic support of evidence. The total support of evidences can be weighted by it and the static support which represent the importance of sensors and the reliability of sensor distribution and importance. $\tilde{Sup}_i = Sup_i * sw_i$. Where the static support parameter is known by the sensor distribution.

$$sw_1 = 1.0000; sw_2 = 0.2040; sw_3 = 1.0000.$$

$$\tilde{Sup}_1 = 0.4746; \tilde{Sup}_2 = 0.0258; \tilde{Sup}_3 = 0.3988;$$

Step 6: The support of evidence is normalized as the final weights W_i

$$W_1 = 0.5278; W_2 = 0.0287; W_3 = 0.4435.$$

Step 7: The weighted average evidence can be calculated by

$$m(\{\cdot\}) = \sum m_i(\{\cdot\}) * Rpe_i.$$

$$m(\{F_1\}) = 0.6285$$

$$m(\{F_2\}) = 0.1201$$

$$m(\{F_1, F_2\}) = 0.0986$$

$$m(\{\Theta\}) = 0.1528$$

Step 8: The modified evidence is combined with 2 times by Dempster's combination rule, and the results of target A is $m_f(\{F_1\}) = (m \oplus m) \oplus m(\{F_1\}) = 0.9023$. The same is available, $m_f(\{F_2\}) = 0.1201$, $m_f(\{F_1, F_2\}) = 0.0986$, $m_f(\{\Theta\}) = 0.1528$. Combination results of different fusion algorithms on the evidence of fault diagnosis are shown in Table 4 and Fig. 5.

As shown in Table 4, the fault type F_1 can be correctly diagnosed with the proposed method. Fan and Zuo's method [10], Yuan et al. [11] and Xiao [9] can correctly diagnose fault F_1 , while the wrong diagnosis results is obtained by Dempster's method [3]. This suggests that improved methods of weakening the degree of conflict in the original evidence have a good effect in dealing with the problem of evidence of serious conflict. Compared with the comparison method, the method proposed in this paper has a highest probability of diagnostic target support (90.23%), which is because weighted credibility

Table 4. Combination results of different fusion algorithms on the evidence of fault diagnosis

Method	$\{F_1\}$	$\{F_2\}$	$\{F_2, F_3\}$	$\{F_1, F_2, F_3\}$	Target
Dempster [3]	0.4519	0.5048	0.0336	0.0096	F_2
Fan et al. [10]	0.8119	0.1096	0.0526	0.0259	F_1
Yuan et al. [11]	0.8948	0.0739	0.0241	0.0072	F_1
Xiao [9]	0.8973	0.0688	0.0254	0.0080	F_1
Proposed method	0.9023	0.0674	0.0235	0.0068	F_1

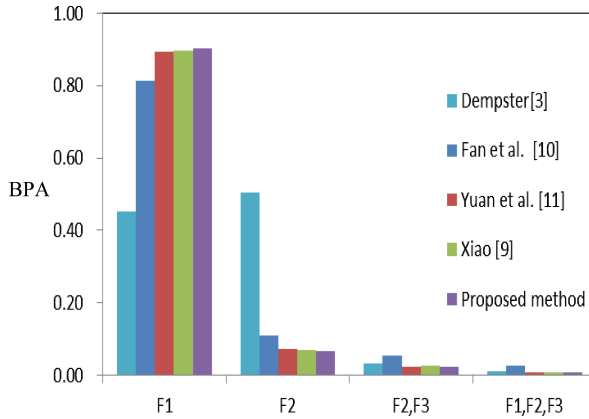


Fig. 5. The comparison of BBAs generated by different methods in Example 2.

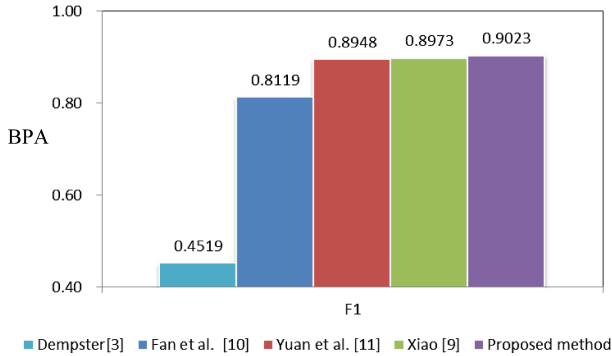


Fig. 6. Probability of fault F_1 being diagnosed

interval and the Sum of Absolute Difference are good measures of the reliability, and the conflict degree between the evidence can be reduced.

As shown in Fig. 6, the proposed method present superior performance with a higher probability (90.23%) on target A compared with the best results in the comparison method. The numerical fusion example is verified that the proposed method is feasible and improved, of which weighted credibility interval can reduce the conflict of evidence. This is because Sum of Absolute Difference can succinctly measure the mutual support between evidences, and credibility interval lengths can effectively measure the reliability of the evidence itself through the distribution of propositions. The proposed method considers both the effect of the two on the final weight to be effective.

4 Conclusion

The comprehensive consideration of the influence of evidence credibility and evidence uncertainty on weight, this paper proposes a new multi-sensor data fusion method based on the weighted credibility interval. The improvement of the method is to propose the weighted credibility interval to weaken the conflict degree between evidences. Specifically, the Sum of Absolute Difference is used to measure the support between any two evidences. On the other hand, the reliability of the evidence itself is measured by the average credibility interval lengths. The two parameters are weighted to obtain the final adjustment weight, and the weighted average evidence is calculated using the adjustment weight and the original evidence. And then Dempster-Shafter combination rule is used to get the final fusion result. Ultimately, the numerical examples illustrate that the proposed method is more effective and feasible than other related methods to handle the conflicting evidence combination problem under multi-sensor environment. Further research work mainly includes the following two aspects. One is the broader study to compare the generalization of uncertainty information in the interval parameter processing. For example, the distance of evidence [12], the joint performance of information entropy [8, 13] and similarity [14]. Second, the use of more practical and difficult verification cases is also of practical significance.

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