Enhance to weaken the conflict evidence using the similarity matrix and dispersion of similarities in Dempster-Shafer evidence theory

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Abstract

Classic Dempster combination rule may result in illogical results when combining highly conflict evidence. How to deal with highly conflict evidence and get a reasonable result is critical. Modifying the evidence is one of significant strategies according to the importance of each evidence (e.g. similarity matrix). However, the dispersion of evidence similarity is rarely taken into consideration, which is also an important feature to distinguish the conflict evidence and normal evidence. In this paper, a new method based on similarity matrix and dispersion of evidence similarity is proposed to evaluate the importance of evidence in Dempster-Shafer theory (DST). The proposed method enhances to weaken the influence of the conflict evidence. Robustness of the proposed method is verified through the sensitivity analysis the

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changes of degree of conflict and amount of credible evidence changes in DST. Some numerical examples are used to show the effectiveness of the proposed method.

Keywords: Dispersion of similarities matrix, Dempster-Shafer evidence theory, Conflict management, Decision making, Information fusion

1. Introduction

Evidence theory has played an important role in decision-making[1–3], information fusion[4–6], risk analysis[7, 8], and so on. Since Dempster-Shafer evidence theory[9, 10] was proposed, how to get a reasonable result has become an important research topic[11–14]. However, under the influence of multiple elements, not all the evidence is reasonable. How to deal with these uncertain and conflict evidence is still a very important issue[15–17]. Once evidence exists, the results obtained by the classic Dempster combination rule are unreasonable[18, 19]. Many people have proposed their methods to resolve conflict evidence[20]. Most literature mainly deals with conflict evidence from two aspects:[21, 22] (1)modify the fusion rules of evidence.[23–29] (2)modify the evidence according to the importance of the evidence.[30–36]

In the first aspect, the main idea is to modify fusion rules of evidence. The Dempster combination rule has played an important role in this development. However, some scholars believe that the Dempster combination rule is very useful in most cases, but when the conflict between the evidence subjects will make the normalization operation in the Dempster combination rule invalid, they advocate improving the fusion rule. Yager[23] thinks that conflict evidence cannot provide useful information and all the basic probability of the conflict part is assigned to the frame of discernment. The method provided by Dubois and Prade[24] distributes all conflict mass functions to all subsets. Smets' method[25, 26], a set of axioms justifying Dempster's rule for the combination of belief functions induced by two distinct pieces of evidence is presented. Sun's method[27], which introduces the credibility between the evidence. Lefevre et al.[28] proposed the concept of a support degree function, which redistributed the local conflicts of evidence to the focal elements involved in the conflict according to the weight. Nimisha et al.[29] propose a combination rule based on weighted Deng entropy.

In the second aspect, the main idea is to modify the evidence according to the importance of the evidence. These scholars believe that the Dempster combination rule is reasonable, and the problem of synthesis lies in the source of evidence itself, so it is necessary to pre-process the evidence. Muyphy[30] proposed an averaging method, which arithmetically averages all evidence sources and then merges them through the Dempster combination rule. Deng[31] proposed a weighted average method based on the similarity measure matrix between the evidence. Han's method[32], ambiguity measure is used as the uncertainty measure to modify the weights generated based on the distance of evidence. Xiong et al.[33] processes the source of evidence-based on the direct and indirect effects of the complex network. Capelle[34] et al. also considered the distance relationship between the evidence and proposed a new method by transforming the basic credibility function. Li and Xiao[35] assign the evidence weight through distance function and Tsallis entropy. Liu and Tang's method[36]. The weight of each belief function is calculated according to the evidence distance to recalculate the revised BPA.

For the first aspect, in most cases, directly modifying the D-S rule does not satisfy the associative law. When there are many sources of evidence, how to determine the subset of conflict allocation is also a problem. It is more feasible to modify the model to re-establish the evidence source. So this paper also contributes to the second category of methods.

Before, Han et al.[37] use Jousselme evidence distance to define the variance of evidence, adjusts the weight through parameter α, and then conducts evidence fusion. But it is mainly used to solve the problem of trust offset. This paper mainly uses the variance of the support degree matrix to adjust the weights, weakens the conflict evidence and enhances the credible evidence. Limited work has been done on the dispersion of evidence similarity, which may provide us a contribution on the conflict management in DST.

According to the analysis of the reliability value between the evidence, we find that conflict evidence is always far from credible evidence. And credible evidence is easier to gather together, so the difference between the support degrees obtained by conflict evidence is small, the variance obtained by the support degree is also small. Credible evidence tends to get greater variance. Based on this, the weight value obtained by each piece of evidence is revised and get more reliable fusion results.

The contribution of the paper is summarized as follows:

(1)Dispersion of similarity matrix is used to enhance to weaken the conflict evidence.

(2)Robustness of the proposed method is verified through the sensitivity analysis the changes of degree of conflict and amount of credible evidence changes in DST.

(3)The proposed method is more practical and effective than previous work.

The rest of this article is structured as follows. The second part introduces some basic knowledge and related work. The third part proposes a new evidence combination method based on the variance of evidence. The fourth part is comparing with previous methods. The fifth part is the sensitivity analysis of this method. The sixth part summarizes the work done in this paper.

2. Preliminaries

In this section, some important definitions needed for further research in Dempster combination rule are introduced. Including Murphy's average method and Deng's weighted average method.

2.1. ***The Dempster combination rule****[9, 10]*

The Theory of Evidence was first proposed by Dempster and further developed by Shafer. It is also called Dempster-Shafer (DST) evidence theory. Evidence theory can flexibly and effectively model uncertainty without prior probability. Evidence theory satisfies a weaker axiom system than probability theory. When the probability value is known, evidence theory becomes probability theory.

There is a fixed set of N mutually exclusive and exhaustive elements, called the frame of discernment, which is symbolized by

$$\Theta = \{H_1, H_2, H_3, \cdots, H_N\}$$

A subset of Θ is called a proposition. The power set of Θ consists of all subsets of Θ contains 2^N elements. It can also be expressed as

$$P(\Theta) = \{\varnothing, \{H_1\}, \{H_2\}, \cdots, \{H_N\}, \{H_1 \cup H_2\}, \{H_1 \cup H_3\}, \cdots, \Theta\} \quad (1)$$

The basic probability assignment(BPA) function or mass function is a mapping from Θ to [0,1]:

$$m : P(\Theta) \to [0, 1] \quad (2)$$

and which satisfies two conditions:

$$\begin{aligned} m(\varnothing) &= 0 \\ \sum_{A \in P(\Theta)} m(A) &= 1 \end{aligned} \quad (3)$$

The value of m(A) indicates the degree to which the evidence supports proposition A. For $A \subseteq P(\Theta)$, if m(A)>0, then call A a focal element. Body of evidence (BOE) is a collection of all focal elements

$$(\mathcal{R}, m) = \{[A, m(A)] \subseteq P(\Theta) \quad and \quad m(A) > 0\} \quad (4)$$

$\mathcal{R}$ is a subset of $P(\Theta)$, and each $A \in \mathcal{R}$ has a fixed value m(A). Two bodies of evidence m_1 and m_2 can be merged with Dempster's orthogonal rule as follows

$$m(A) = \frac{\sum\limits_{B \cap C = A} m_1(B) m_2(C)}{1 - K} \quad (5)$$

where

$$K = \sum_{B \cap C = \varnothing} m_1(B) m_2(C) \tag{6}$$

Where K is the conflict coefficient, the closer K is to 1, the more serious the conflict between the evidence sources, and the closer K is to 0, the more consistent the evidence sources are.

2.1.1. The Distance Of Evidence[38, 39]

To describe the differences between different evidence, the distance of evidence is also an important part. The vector space in which the distance is defined is called the metric space. The distance on the vector space S is defined as follows:

$$d : S \times S \to R \tag{7}$$

The distance d satisfies the following conditions($\forall A, B \in S$):

$$\begin{gathered} d(A,B) \geq 0 \quad when \quad A = B \quad d(A,B) = 0 \\ d(A,B) = d(B,A) \\ d(A,B) \leq d(A,C) + d(C,B), \forall C \in S \end{gathered} \tag{8}$$

The formula for calculating the distance between two evidence bodies is as follows:

$$d(m_1, m_2) = (\vec{m_1} - \vec{m_1})^T \underline{\underline{D}} (\vec{m_1} - \vec{m_1}) \tag{9}$$

The commonly used calculation formula is:

$$d_{BPA}(m_1, m_2) = \sqrt{\frac{1}{2} (\vec{m_1} - \vec{m_1})^T \underline{\underline{D}} (\vec{m_1} - \vec{m_1})} \tag{10}$$

$\vec{m}_1$ and $\vec{m}_2$ represent the vector formed by the BPA of the two sources of evidence. $\underline{\underline{D}}$ is a $2^N \times 2^N$ matrix. The row index of $\underline{\underline{D}}$ corresponds to evidence source 1, and the column index corresponds to evidence source 2. Each element in $\underline{\underline{D}}$ is

$$\underline{\underline{D}}(A, B) = \frac{|A \cap B|}{|A \cup B|} \tag{11}$$

$|A|$ represents the cardinality of set A, that is, the number of elements in the set A.

2.1.2. Belief Function and Plausibility Function[9, 10]

The belief function is defined as follows:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad \forall A \subseteq \Theta \tag{12}$$

$Bel(A)$ represents the total level of trust in A. According to the characteristics of the basic probability distribution function, we can know:

$$\begin{aligned} Bel(\varnothing) &= m(\varnothing) = 0 \\ Bel(\Theta) &= \sum_{B \subseteq \Theta} m(B) = 1 \end{aligned} \tag{13}$$

The plausibility function is defined as follows:

$$Pl(A) = \sum_{B \cap A \neq \varnothing} m(B) \quad \forall A \subseteq \Theta \tag{14}$$

The plausibility function can also be expressed as:

$$Pl(A) = 1 - Bel(\overline{A}) \tag{15}$$

The plausibility function represents the degree of trust that does not deny A. The plausibility function has the following characteristics:

$$\begin{aligned} Pl(\varnothing) &= 0 \\ Pl(\Theta) &= 1 \end{aligned} \tag{16}$$

The relationship between plausibility function and belief function:

$$Pl(A) \geq Bel(A) \tag{17}$$

2.1.3. Zadeh paradox[18]

According to Eq.(6), we can get the conflict coefficient K. When $K \to 1$, indicates that the evidence is highly conflict. At this time, using the Dempster combination rule will get counter-intuitive results. Moreover, even if the number of consistent information sources is increased, the conflict coefficient K cannot be reduced.

The three criminal suspects of a certain under case constitute the frame of discernment $\Theta = \{Peter, Paul, Mary\}$, and the witnesses $S1$ and $S2$ respectively give the following BPAs:

$$m_1(Peter) = 0.99, m_1(Paul) = 0.01, m_1(Mary) = 0.00$$

$$m_1(Peter) = 0.00, m_1(Paul) = 0.01, m_1(Mary) = 0.99$$

By using Dempster combination rule, we can get the following results: $m_1 \oplus m_2(Peter) = 0.00$, $m_1 \oplus m_2(Paul) = 1.00$ and $m_1 \oplus m_2(Mary) = 0.00$. This shows that Paul is the murderer, obviously not in line with the logic of fact. Therefore, when the evidence is highly conflict, the Dempster combination rule often results in counter-intuitive results.

2.2. ***Murphy's average approach[30]***

From the averaging method proposed by Murphy, we can know that, if there is sufficient evidence at the same time, the quality can be averaged, and the comprehensive masses can be calculated by combining the average multiple times. And Voorbraak pointed that[10] combined with other evidence, the probability assigned to the set is not divided into its elements, but is consistent with all elements. This property can cause an element in a multi-element set to receive a greater belief than it seems reasonable. The result of Murphy's averaging approach seems more reasonable than that of combination without averaging. The specific process is as follows:

$$\begin{aligned} m^1 &= f_{D-S}(m_a, m_a) \\ m^i &= f_{D-S}(m^{i-1}, m_a), \quad i \geq 2 \end{aligned} \tag{18}$$

Assuming there are n sources of evidence, this method first averages the BPA of the n sources of evidence to obtain m_a. Then use the Dempster combination rule to iterate (n-1) times for m_a to obtain the final BPA.

2.3. ***Deng's method[31]***

First calculate the distance between the two evidence bodies $(\mathcal{R}_i, m_i)$ and $(\mathcal{R}_j, m_j)$. The similarity measure Sim_{ij} between $(\mathcal{R}, m_i)$ and $(\mathcal{R}, m_j)$ is defined as:

$$Sim(m_i, m_j) = 1 - d(m_i, m_j) \tag{19}$$

According to Eq.(10), the smaller the distance between the two evidence bodies, the more similar the two evidence bodies are. Suppose the number of bodies of evidence is n. The support degree of the body of evidence $(\mathcal{R}_i, m_i)(i = 1, 2, ..., n)$ is defined as:

$$Sup(m_i) = \sum_{j=1 \quad j \neq i}^{n} Sim(m_i, m_j) \tag{20}$$

After knowing the distance between every two evidence bodies, a similarity measure matrix(SMM) can be constructed, which can help us better understand the agreement between the bodies of evidence.

The credibility degree Crd_i of the body of evidence $(\mathcal{R}_i, m_i)(i = 1, 2, ..., n)$ is defined as:

$$Crd_i = \frac{Sup(m_i)}{\sum\limits_{i=1}^{n} Sup(m_i)} \tag{21}$$

We can easily see that $\sum\limits_{i=1}^{n} Crd_i = 1$. And the credibility degree weight shows the relative importance of the collected evidence.

So we can get the modified average (or the weighted average) of the evidence MAE:

$$MAE(m) = \sum_{i=1}^{n} (Crd_i \times m_i) \tag{22}$$

If there are n pieces of evidence, we need to use the Dempster combination rule to iterate the weighted average of the masses $n - 1$ times to obtain the final BPA. It is like Murphy's method.

3. The proposed method

First of all, according to the minority obeying the majority, we believe that most of the evidence supports the final result, while the conflict evidence is contrary to the final result. In other words, because most of the evidence supports the same result, the similarity measure of these pieces of evidence is relatively large. According to Eq.(19), the evidence distance of these evidence is much smaller than that of conflict evidence. As shown in Figure 1. We assume that there are five bodies of evidence, where m_2 is conflict evidence.

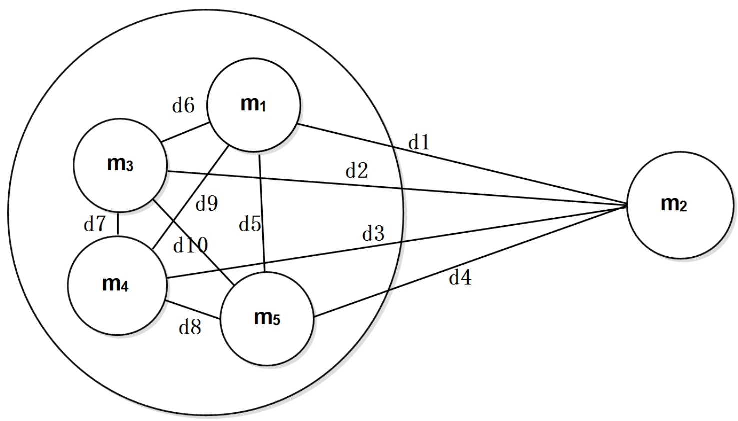

Figure 1. Distance Histogram

Because the bodies of evidence m1, m3, m4, and m5 uniformly support the final result, but m2 is far away from them as evidence of conflict. In order to better reflect the relationship between the evidence, as shown in Figure 2.

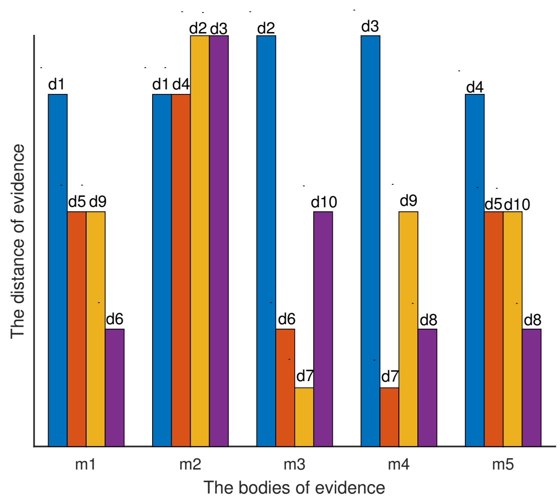

Figure 2. Distance Histogram

From the Figure 2, we can see that in addition to the distance obtained by m2, the distance obtained by other evidence is too large or too small. As a result, the obtained distance data fluctuates greatly, that is, the variance is large. Compared with these pieces of evidence, the distance data of m2 fluctuates significantly, that is, the variance is small. Based on this, this article mainly starts with the variance and uses the positive feedback method to modify the weight of each piece of evidence. As follows:

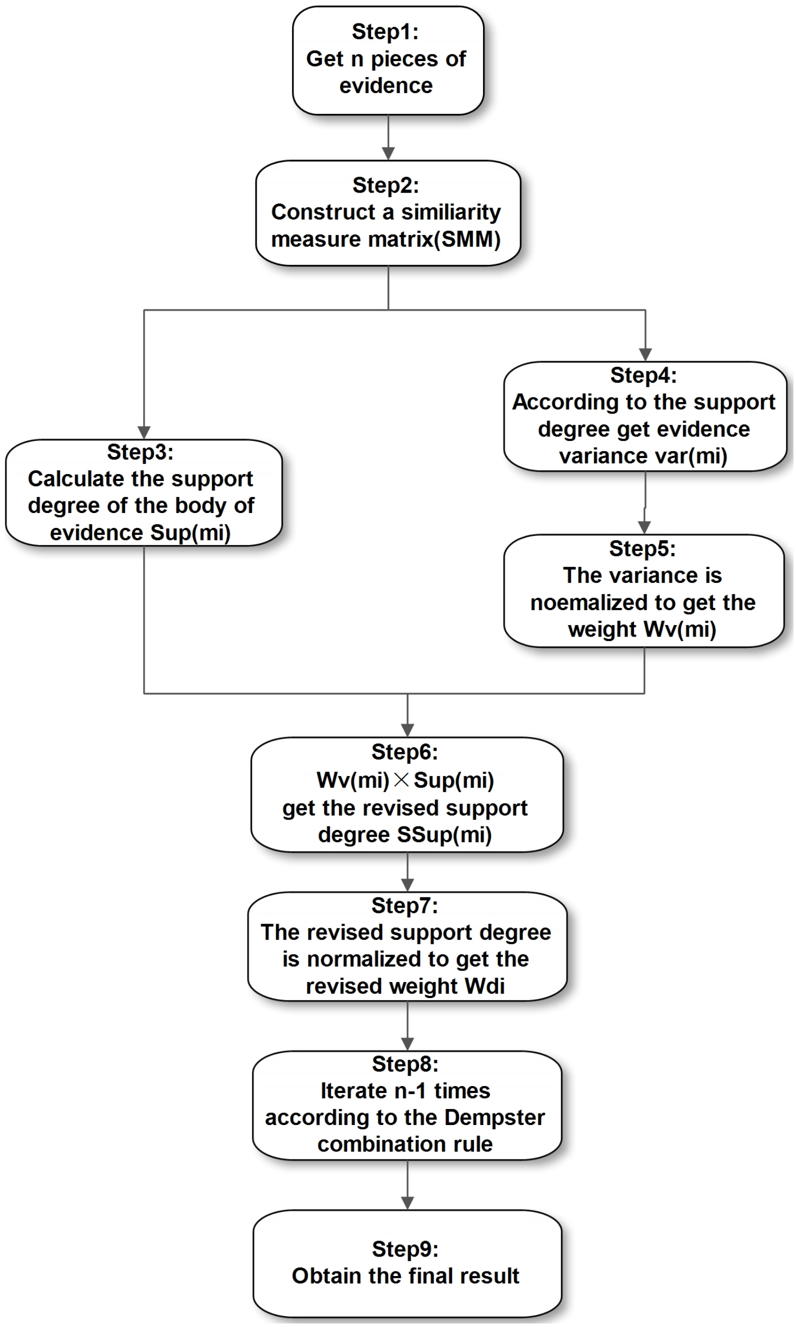

Figure 3. Framework of the proposed method

(1)According to Eq.(6), calculate the distance between every two pieces of evidence bodies $d(m_i, m_j)$.

(2)According to Eq.(19), calculate the similarity measure between every two evidence bodies $Sim(m_i, m_j)$. According to Eq.(20), calculate the support degree of the body of evidence $Sup(m_i)$.

(3)Regardless of its influence, each evidence body can obtain $n-1$ evidence similarity measures, and calculate the variance of these $n-1$ similarity measures.

$$var(m_i) = \frac{\sum\limits_{j=1}^{n} \sum\limits_{j \neq i} (Sim(m_i, m_j) - \overline{Sim(m_i, m_j)})^2}{n-1} \tag{23}$$

where $\overline{Sim(m_i, m_j)} = \frac{\sum\limits_{j=1}^{n} \sum\limits_{j \neq i} Sim(m_i, m_j)}{n-1}$ is the average of $n-1$ similarity measures.

(4)Revise the weight of evidence by variance:

$$Wv(m_i) = \frac{var(m_i)}{\sum\limits_{i=1}^{n} var(m_i)} \tag{24}$$

(5)Modified the support degree of the body of evidence $(\mathcal{R}_i, m_i)(i = 1, 2, ..., n)$:

$$SSup(m_i) = Wv(m_i) \times Sup(m_i) \tag{25}$$

(6)The credibility degree Wd_i of the body of evidence $(\mathcal{R}_i, m_i)(i = 1, 2, ..., n)$ is:

$$Wd_i = \frac{SSup(m_i)}{\sum\limits_{i=1}^{n} SSup(m_i)} \tag{26}$$

(7)The modified probability (or the weighted average) of the evidence MAE is given as:

$$MAE = \sum_{i=1}^{n}(m_i \times Wd_i) \tag{27}$$

(8)If there are n pieces of evidence, we only need to iterate n-1 times according to the Dempster combination rule.

If one piece of evidence has a greater degree of support than other pieces of evidence, its similarity measure is higher, the variance is greater, and the evidence will have a greater impact on the final combined result. On the contrary, if a certain piece of evidence always conflicts with other evidence, its similarity measure is lower, and the variance is smaller, and the evidence has less influence on the final combined result. We use this positive feedback method of variance to further strengthen the more credible evidence and further weaken the less credible evidence.

4. Comparing with previous methods

The following examples are mainly verified from two parts. The first part mainly verifies: Use classic examples in other articles for fusion, and compare and analyze with others' methods. The second part mainly verifies: The analysis is mainly conducted from two aspects: the change in the degree of conflict of evidence and the change in the quantity between conflict evidence and credible evidence.

4.1. Numerical examples to compare with previous methods

Example 1. In the automatic target recognition system based on multiple sensors, assumed the real target is A. From five different sensors, the system has collected five bodies of evidence shown as follows:[31]

$$\begin{aligned}
(\mathcal{R}_1, m_1) = &\quad ([\{A\}, 0.50], [\{B\}, 0.20], [\{C\}, 0.30]) \\
(\mathcal{R}_2, m_2) = &\quad ([\{A\}, 0.00], [\{B\}, 0.90], [\{C\}, 0.10]) \\
(\mathcal{R}_3, m_3) = &\quad ([\{A\}, 0.55], [\{B\}, 0.10], [\{A, C\}, 0.35]) \\
(\mathcal{R}_4, m_4) = &\quad ([\{A\}, 0.55], [\{B\}, 0.10], [\{A, C\}, 0.35]) \\
(\mathcal{R}_5, m_5) = &\quad ([\{A\}, 0.60], [\{B\}, 0.10], [\{A, C\}, 0.30])
\end{aligned}$$

It is easy to see that evidence m2 conflicts with other evidence. So we hope to reduce the influence of m2 on the fusion result. Five pieces of evidence of five sensors are taken as the point set. The specific calculation process is as follows:

Step 1. construct a similarity measure matrix based on the distance between the evidence bodies. As followed:

$$[SMM] = \begin{bmatrix} 1.0000 & 0.3755 & 0.7378 & 0.7378 & 0.7354 \\ 0.3755 & 1.0000 & 0.2150 & 0.2150 & 0.2094 \\ 0.7378 & 0.2150 & 1.0000 & 1.0000 & 0.9646 \\ 0.7378 & 0.2150 & 1.0000 & 1.0000 & 0.9646 \\ 0.7354 & 0.2094 & 0.9646 & 0.9646 & 1.0000 \end{bmatrix} \tag{28}$$

Step 2. calculate the support degree of the body of evidence.

$Sup(m_1) = 0.3755 + 0.7378 + 0.7378 + 0.7354 = 2.5865,$

$Sup(m_2) = 1.0149$, $Sup(m_3) = 2.9174,$

$Sup(m_4) = 2.9174$, $Sup(m_5) = 2.8741$.

Step 3. calculate the variance of these $n-1$ similarity measures.

$\overline{Sim(m_1, m_j)} = \frac{0.3755+0.7378+0.7378+0.7354}{4} = 0.646625$,

$var(m_1) = 0.0245$,

$var(m_2) = 0.0049$,

$var(m_3) = 0.0983$,

$var(m_4) = 0.0983$,

$var(m_5) = 0.0951$.

Step 4. calculate the weight of evidence by variance:

$Wv(m_1) = \frac{0.0245}{0.0245+0.0049+0.0983+0.0983+0.0951} = 0.0763$,

$Wv(m_2) = 0.0153$, $Wv(m_3) = 0.3061$,

$Wv(m_4) = 0.3061$, $Wv(m_5) = 0.2962$.

Step 5. calculate modified support degree of the body of evidence $(\mathcal{R}_i, m_i)(i = 1, 2, ..., n)$:

$SSup(m_1) = Wv(m_1) \times Sup(m_1) = 0.0763 \times 2.5865 = 0.1973$,

$SSup(m_2) = 0.0155$, $SSup(m_3) = 0.8930$,

$SSup(m_4) = 0.8930$, $SSup(m_5) = 0.8513$.

Step 6. calculate the credibility degree Wd_i of the body of evidence $(\mathcal{R}_i, m_i)(i = 1, 2, ..., n)$:

$Wd_1 = \frac{0.1973}{0.1973+0.0155+0.8930+0.8930+0.8513} = 0.0692$,

$Wd_2 = 0.0054$, $Wd_3 = 0.3133$,

$Wd_4 = 0.3133$, $Wd_5 = 0.2987$.

Step 7. calculate the modified probability of the evidence MAE, then need to iterate 4 times according to the Dempster combination rule.

The final weight obtained for each piece of evidence is shown in the figure below(Take five pieces of evidence as examples):

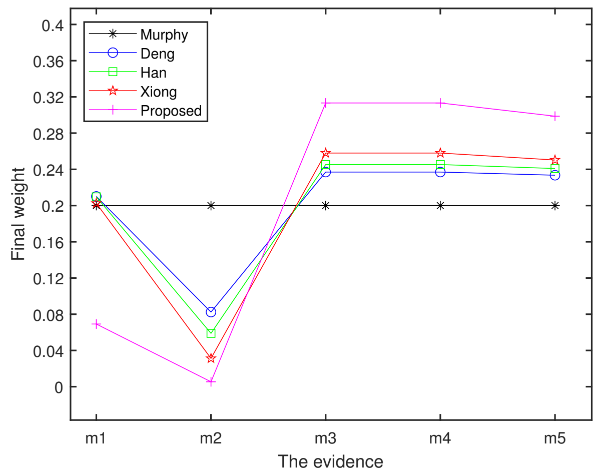

Figure 4. The final weight of each piece of evidence.

The final result is shown in the table below:

Table 1: Results of different combination rules of evidence

Approach	m_1, m_2	m_1, m_2, m_3	m_1, m_2, m_3, m_4	m_1, m_2, m_3, m_4, m_5
Dempster combination rule[9, 10]	m(A)=0.0000 m(B)=0.8571 m(C)=0.1429	m(A)=0.0000 m(B)=0.6316 m(C)=0.3684	m(A)=0.0000 m(B)=0.3288 m(C)=0.6712	m(A)=0.0000 m(B)=0.1228 m(C)=0.8772
Murphy's method[30]	m(A)=0.1543 m(B)=0.7469 m(C)=0.0988	m(A)=0.5569 m(B)=0.3562 m(C)=0.0781 m(A C)=0.0088	m(A)=0.8653 m(B)=0.0891 m(C)=0.0382 m(A C)=0.0075	m(A)=0.9688 m(B)=0.0156 m(C)=0.0127 m(A C)=0.0029
Deng's method[31]	m(A)=0.1543 m(B)=0.7469 m(C)=0.0988	m(A)=0.7369 m(B)=0.1618 m(C)=0.0915 m(A C)=0.0098	m(A)=0.9484 m(B)=0.0120 m(C)=0.0310 m(A C)=0.0086	m(A)=0.9869 m(B)=0.0010 m(C)=0.0088 m(A C)=0.0032
Han's method[32]	m(A)=0.1543 m(B)=0.7469 m(C)=0.0988	m(A)=0.7871 m(B)=0.1092 m(C)=0.0936 m(A C)=0.0098	m(A)=0.9558 m(B)=0.0063 m(C)=0.0291 m(A C)=0.0088	m(A)=0.9880 m(B)=5.1375e-04 m(C)=0.0081 m(A C)=0.0033
Xiong's method[33]	m(A)=0.1543 m(B)=0.7469 m(C)=0.0988	m(A)=0.7990 m(B)=0.0602 m(C)=0.1402 m(A C)=6.0712e-04	m(A)=0.9610 m(B)=0.0031 m(C)=0.0268 m(A C)=0.0091	m(A)=0.9891 m(B)=2.0706e-04 m(C)=0.0072 m(A C)=0.0035
Proposed method	m(A)=0.1543 m(B)=0.7469 m(C)=0.0988	m(A)=0.9079 m(B)=0.0105 m(C)=0.0573 m(A C)=0.0243	m(A)=0.9732 m(B)=3.9023e-04 m(C)=0.0093 m(A C)=0.0171	m(A)=0.9920 m(B)=3.4659e-05 m(C)=0.0023 m(A C)=0.0057

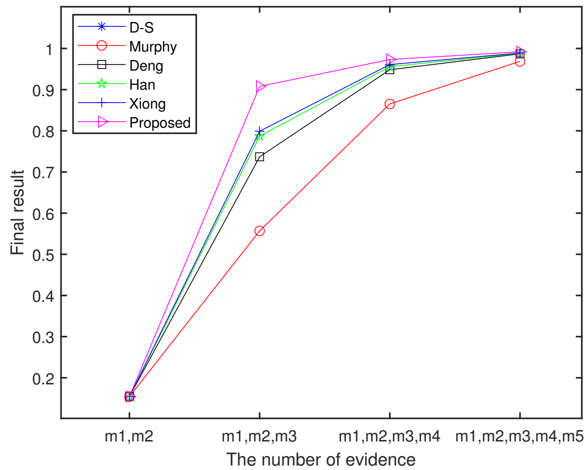

Figure 5. Convergence effect of m(A) in the composite result

Example 2. Assuming that the multi-sensor collaborative detection target {a b c}[40] produces five pieces of detection information, which are transformed into the evidence theory framework system, the five pieces of evidence to be fused are as follows:

$$(\mathcal{R}_1, m_1) = \quad ([\{A\}, 0.65], [\{B\}, 0.20], [\{C\}, 0.15])$$
$$(\mathcal{R}_2, m_2) = \quad ([\{A\}, 0.00], [\{B\}, 0.75], [\{C\}, 0.25])$$
$$(\mathcal{R}_3, m_3) = \quad ([\{A\}, 0.70], [\{B\}, 0.05], [\{C\}, 0.25])$$
$$(\mathcal{R}_4, m_4) = \quad ([\{A\}, 0.80], [\{B\}, 0.15], [\{C\}, 0.05])$$
$$(\mathcal{R}_5, m_5) = \quad ([\{A\}, 0.75], [\{B\}, 0.20], [\{C\}, 0.05])$$

It is clear from the evidence that A is the real target. Due to various reasons, the second piece of evidence conflicts with other evidence.

The final weight obtained for each piece of evidence is shown in the figure below(Take five pieces of evidence as examples):

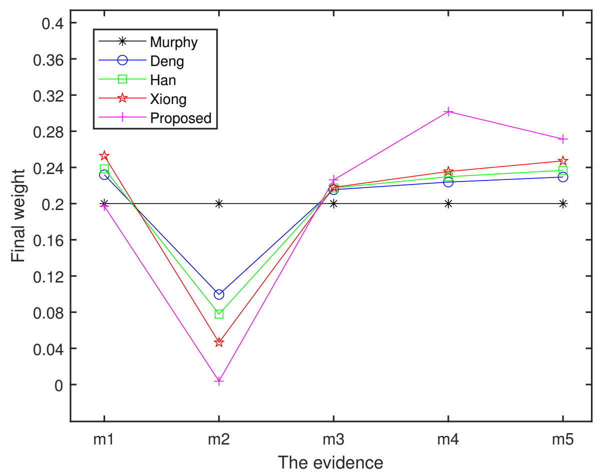

Figure 6. The final weight of each piece of evidence.

The final result is shown in the table below:

Table 2: Results of different combination rules of evidence

Approach	m_1, m_2	m_1, m_2, m_3	m_1, m_2, m_3, m_4	m_1, m_2, m_3, m_4, m_5
Dempster combination rule[9, 10]	m(A)=0.0000 m(B)=0.8000 m(C)=0.2000	m(A)=0.0000 m(B)=0.4444 m(C)=0.5556	m(A)=0.0000 m(B)=0.7059 m(C)=0.2941	m(A)=0.0000 m(B)=0.9057 m(C)=0.0943
Murphy‘ method[30]	m(A)=0.2845 m(B)=0.6077 m(C)=0.1077	m(A)=0.6588 m(B)=0.2677 m(C)=0.0736	m(A)=0.9148 m(B)=0.0749 m(C)=0.0103	m(A)=0.9775 m(B)=0.0214 m(C)=0.0011
Deng's method[31]	m(A)=0.2845 m(B)=0.6077 m(C)=0.1077	m(A)=0.8371 m(B)=0.1094 m(C)=0.0535	m(A)=0.9794 m(B)=0.0157 m(C)=0.0049	m(A)=0.9961 m(B)=0.0035 m(C)=3.9403e-04
Han's method[32]	m(A)=0.2845 m(B)=0.6077 m(C)=0.1077	m(A)=0.8789 m(B)=0.0744 m(C)=0.0468	m(A)=0.9862 m(B)=0.0098 m(C)=0.0040	m(A)=0.9974 m(B)=0.0023 m(C)=3.0942e-04
Xiong's method[33]	m(A)=0.2845 m(B)=0.6077 m(C)=0.1077	m(A)=0.9118 m(B)=0.0485 m(C)=0.0398	m(A)=0.9915 m(B)=0.0054 m(C)=0.0032	m(A)=0.9985 m(B)=0.0012 m(C)=2.1976e-04
Proposed method	m(A)=0.2845 m(B)=0.6077 m(C)=0.1077	m(A)=0.9661 m(B)=0.0055 m(C)=0.0284	m(A)=0.9970 m(B)=0.0012 m(C)=0.0018	m(A)=0.9995 m(B)=4.0063e-04 m(C)=9.8971e-05

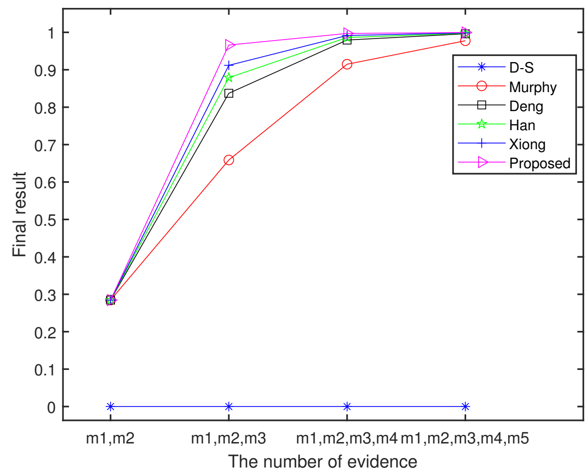

Figure 7. Convergence effect of m(A) in the composite result

Example 3. In a multi-sensor-based target recognition system, there are types of targets: $\Theta = \{A, B, C\}$. There are five different sensors including CCD(S1), audio sensor system (S2), infrared system (S3), Reader (S4), and ESM (S5). From five different sensors, the system has acquired five evidence listed as follows:[32]

S1:$(\mathcal{R}_1, m_1) = \quad ([\{A\}, 0.41], [\{B\}, 0.29], [\{C\}, 0.30])$

S2:$(\mathcal{R}_2, m_2) = \quad ([\{A\}, 0.00], [\{B\}, 0.90], [\{C\}, 0.10])$

S3:$(\mathcal{R}_3, m_3) = \quad ([\{A\}, 0.58], [\{B\}, 0.07], [\{A, C\}, 0.35])$

S4:$(\mathcal{R}_4, m_4) = \quad ([\{A\}, 0.55], [\{B\}, 0.10], [\{A, C\}, 0.35])$

S5:$(\mathcal{R}_5, m_5) = \quad ([\{A\}, 0.60], [\{B\}, 0.10], [\{A, C\}, 0.30])$

It is clear from the evidence that A is the real target.

The final weight obtained for each piece of evidence is shown in the figure below(Take five pieces of evidence as examples):

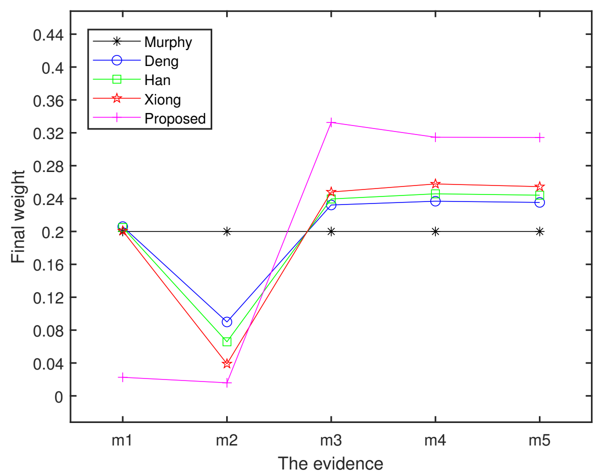

Figure 8. The final weight of each piece of evidence.

The final result is shown in the table below:

Table 3: Results of different combination rules of evidence

Approach	m_1, m_2	m_1, m_2, m_3	m_1, m_2, m_3, m_4	m_1, m_2, m_3, m_4, m_5
Dempster combination rule[9, 10]	m(A)=0.0000 m(B)=0.8969 m(C)=0.1031	m(A)=0.0000 m(B)=0.6575 m(C)=0.3425	m(A)=0.0000 m(B)=0.3321 m(C)=0.6679	m(A)=0.0000 m(B)=0.1422 m(C)=0.8578
Murphy's method[30]	m(A)=0.0964 m(B)=0.8119 m(C)=0.0917	m(A)=0.4939 m(B)=0.4180 m(C)=0.0792 m(A C)=0.0090	m(A)=0.8362 m(B)=0.1147 m(C)=0.0410 m(A C)=0.0081	m(A)=0.9620 m(B)=0.0210 m(C)=0.0138 m(A C)=0.0032
Deng's method[31]	m(A)=0.0964 m(B)=0.8119 m(C)=0.0917	m(A)=0.6021 m(B)=0.2907 m(C)=0.0991 m(A C)=0.0082	m(A)=0.9330 m(B)=0.0225 m(C)=0.0354 m(A C)=0.0092	m(A)=0.9851 m(B)=0.0017 m(C)=0.0096 m(A C)=0.0035
Han's method[32]	m(A)=0.0964 m(B)=0.8119 m(C)=0.0917	m(A)=0.6500 m(B)=0.2355 m(C)=0.1065 m(A C)=0.0079	m(A)=0.9444 m(B)=0.0128 m(C)=0.0334 m(A C)=0.0093	m(A)=0.9867 m(B)=9.0327e-04 m(C)=0.0088 m(A C)=0.0036
Xiong's method[33]	m(A)=0.0964 m(B)=0.8119 m(C)=0.0917	m(A)=0.6667 m(B)=0.2098 m(C)=0.1171 m(A C)=0.0064	m(A)=0.9523 m(B)=0.0069 m(C)=0.0313 m(A C)=0.0095	m(A)=0.9881 m(B)=0.0004 m(C)=0.0078 m(A C)=0.0037
Proposed method	m(A)=0.0964 m(B)=0.8119 m(C)=0.0917	m(A)=0.8954 m(B)=0.0325 m(C)=0.0326 m(A C)=0.0395	m(A)=0.9759 m(B)=3.7110e-04 m(C)=0.0041 m(A C)=0.0197	m(A)=0.9928 m(B)=2.5883e-05 m(C)=8.6036e-04 m(A C)=0.0063

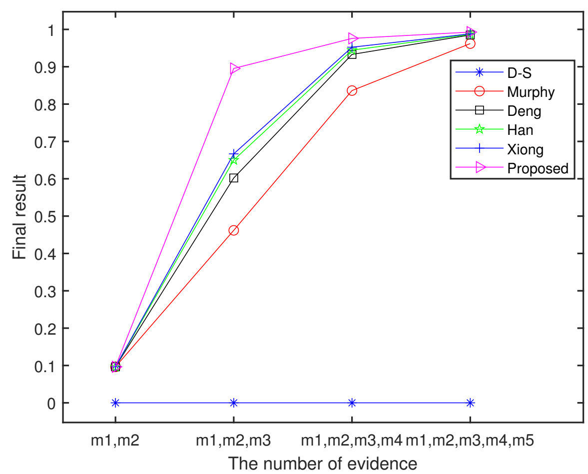

Figure 9. Convergence effect of m(A) in the composite result

4.2. Effectiveness of the proposed method

Analysis of the results obtained from the three examples, when highly conflict evidence appears in a set of evidence, the result of fusion through the classic Dempster combination rule is contrary to our intuition. To obtain a more reasonable fusion result and weaken the influence of conflict evidence on the final result, the other five methods deal with conflict evidence from different perspectives. According to the minority obeying the majority, each method gives reasonable results. From Figure 4, Figure 6, and Figure 8, we can see that the more reliable evidence gets more weight, the more conflict evidence gets less weight. What's more, when there is only one conflict evidence in the data. The conflict evidence has been greatly weakened. And when there are two pieces of conflict evidence, two pieces of conflict evidence have also been weakened. And each example greatly enhances the influence of reasonable evidence on the final result. This only needs to ensure that the amount of reasonable evidence is greater than the amount of conflict evidence. From the data in Table 1, Table 2, and Table 3, it can be seen that the results obtained by the method proposed in this paper is more effective.

For Example 1 and Example 3, m1 gets a small weight, which is weakened by us as conflict evidence. In comparison, it seems that m1 is supporting A, but there is no obvious difference in the degree of support for B and C. And we can also analyze from the conflict coefficient K, as shown in the Table 4(use Example 3 for illustration):

Table 4: Conflict coefficient K between two pieces of conflict evidence

	m_1	m_2	m_3	m_4	m_5
m1	0.6578	0.7090	0.4934	0.4970	0.5120
m2		0.1800	0.9020	0.8750	0.8800
m3			0.1302	0.1560	0.1560
m4				0.1800	0.1800
m5					0.1800

From Table 4, we can see that, the last three sets of evidence are more clustered together, while m2 has obvious conflicts. The most dangerous evidence is m1. Because m1 not only has a higher conflict coefficient with the last three sets of evidence, but also has a higher conflict with itself. In other words, there are high conflicts in the results of self-fusion. So we will definitely not prioritize such evidence. According to the principle of the minority obeys the majority, the last three sets of evidence are more credible, so we weaken the influence of m1 on the final result. There is a clear conflict between m1 and m2 and the last three sets of evidence. So the final result should be closer to the results of the last three sets of evidence.

5. Sensitivity analysis

5.1. Sensitivity changing with the degree of conflict of evidence.

Example 4. The change in the degree of conflict of evidence.

Through a special fictional example, when there are two pieces of evidence whose support degree can be close to 0 and keep changing with α, to show the use of the proposed combination rule. The five pieces of evidence collected by the system are as follows:

S1:$(\mathcal{R}_1, m_1) =$ $([\{A\}, 0.98{-}0.1\alpha], [\{B\}, 0.01{+}0.05\alpha], [\{C\}, 0.01{+}0.05\alpha])$

S2:$(\mathcal{R}_2, m_2) =$ $([\{A\}, 0.01{+}0.05\alpha], [\{B\}, 0.98{-}0.1\alpha], [\{C\}, 0.01{+}0.05\alpha])$

S3:$(\mathcal{R}_3, m_3) =$ $([\{A\}, 1/3], [\{B\}, 1/3], [\{C\}, 1/3])$

S4:$(\mathcal{R}_4, m_4) =$ $([\{A\}, 1/3], [\{B\}, 1/3], [\{C\}, 1/3])$

S5:$(\mathcal{R}_5, m_5) =$ $([\{A\}, 1/3], [\{B\}, 1/3], [\{C\}, 1/3])$

α as a variable, reflecting the change in support degree between evidence.

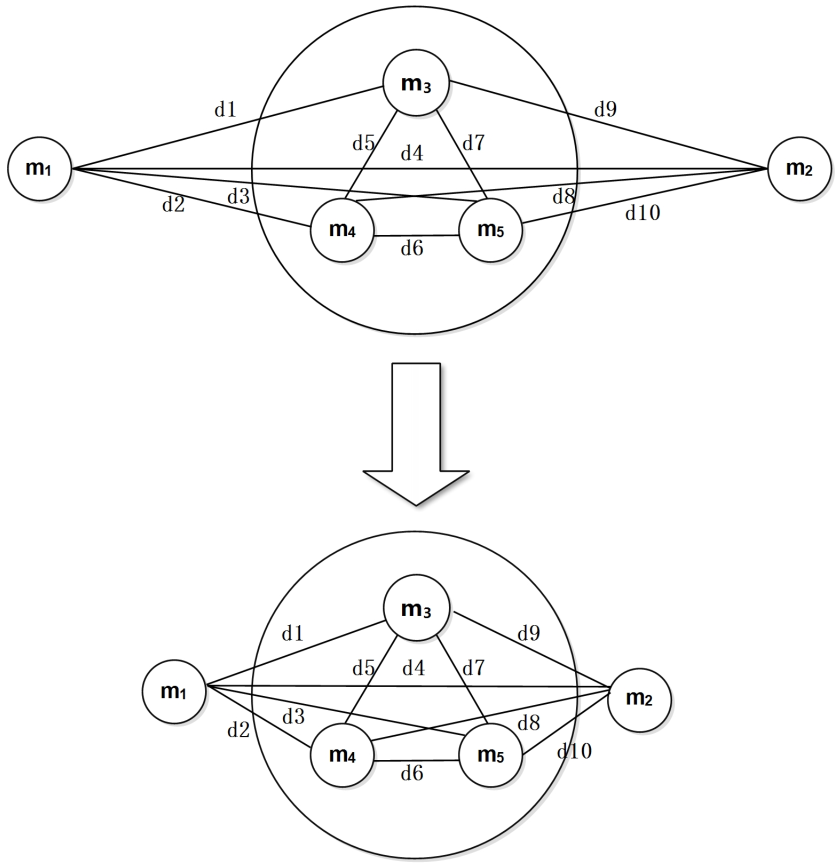

Figure 10. Evidence conflict degree change diagram.

The final weight obtained for each piece of evidence is shown in the figure below(Take five pieces of evidence as examples):

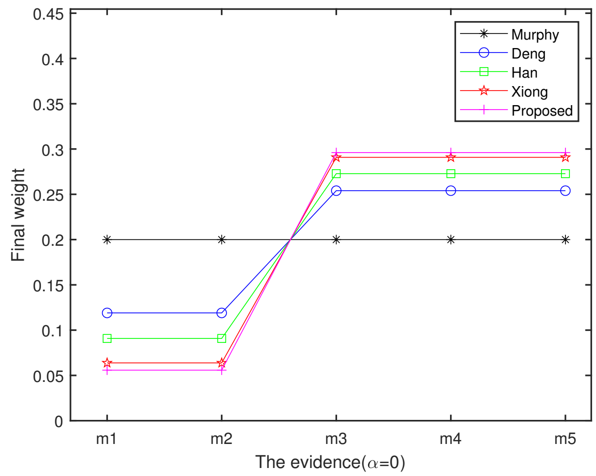

Figure 11. The final weight of each piece of evidence.

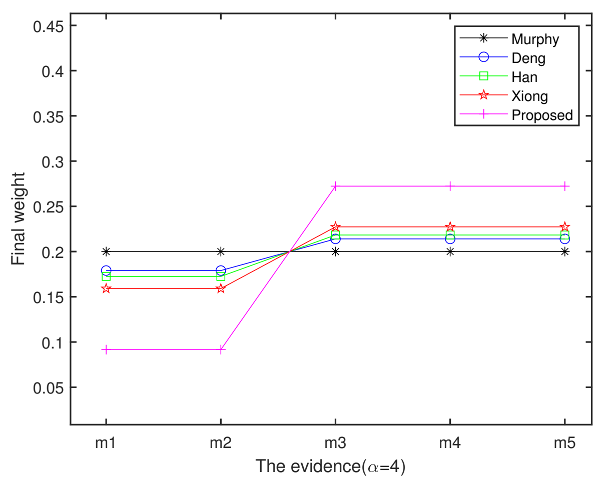

Figure 12. The final weight of each piece of evidence.

The final result is shown in the table below: (m1,m2,m3,m4,m5)

Table 5: Results of different combination rules of evidence

Approach	$\alpha = 0$	$\alpha = 1$	$\alpha = 2$	$\alpha = 3$	$\alpha = 4$
Dempster combination rule[9, 10]	m(A)=0.4975 m(B)=0.4975 m(C)=0.0050	m(A)=0.4835 m(B)=0.4835 m(C)=0.0330	m(A)=0.4671 m(B)=0.4671 m(C)=0.0659	m(A)=0.4474 m(B)=0.4474 m(C)=0.1053	m(A)=0.4234 m(B)=0.4234 m(C)=0.1533
Murphy's method[30]	m(A)=0.4913 m(B)=0.4913 m(C)=0.0174	m(A)=0.4845 m(B)=0.4845 m(C)=0.0311	m(A)=0.4735 m(B)=0.4735 m(C)=0.0531	m(A)=0.4566 m(B)=0.4566 m(C)=0.0868	m(A)=0.4321 m(B)=0.4321 m(C)=0.1358
Deng's method[31]	m(A)=0.4639 m(B)=0.4639 m(C)=0.0723	m(A)=0.4629 m(B)=0.4629 m(C)=0.0742	m(A)=0.4564 m(B)=0.4564 m(C)=0.0872	m(A)=0.4441 m(B)=0.4441 m(C)=0.1119	m(A)=0.4243 m(B)=0.4243 m(C)=0.1513
Han's method[32]	m(A)=0.4447 m(B)=0.4447 m(C)=0.1107	m(A)=0.4529 m(B)=0.4529 m(C)=0.0941	m(A)=0.4498 m(B)=0.4498 m(C)=0.1003	m(A)=0.4397 m(B)=0.4397 m(C)=0.1206	m(A)=0.4218 m(B)=0.4218 m(C)=0.1564
Xiong's method[33]	m(A)=0.4197 m(B)=0.4197 m(C)=0.1606	m(A)=0.4324 m(B)=0.4324 m(C)=0.1352	m(A)=0.4355 m(B)=0.4355 m(C)=0.1290	m(A)=0.4303 m(B)=0.4303 m(C)=0.1394	m(A)=0.4164 m(B)=0.4164 m(C)=0.1672
Proposed method	m(A)=0.4110 m(B)=0.4110 m(C)=0.1781	m(A)=0.4118 m(B)=0.4118 m(C)=0.1764	m(A)=0.4074 m(B)=0.4074 m(C)=0.1851	m(A)=0.3985 m(B)=0.3985 m(C)=0.2030	m(A)=0.3852 m(B)=0.3852 m(C)=0.2296

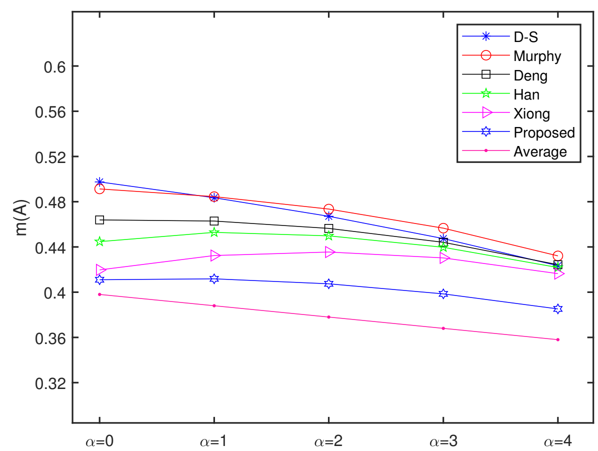

Figure 13. Convergence effect of m(A) in the composite result

Through the last three sets of evidence, the overall support target cannot be distinguished. Considering the overall situation, it is obvious that the support for A and B is greater than that for C. According to the minority obeying the majority, the final result should be closer to the results of the last three pieces of evidence. From Table 5 and Figure 13, we can see that as α increases, the results of our proposed method are still closest to the final results. From Figure 11 and Figure 12, the smaller the α, the stronger we weaken the conflict evidence and credible evidence gets more weight. This shows that though the change in the degree of conflict of evidence, our method is still effective.

5.2. Sensitivity changing with the amount of credible evidence.

Example 5. The change in the quantity between conflict evidence and credible evidence.

When the conflict evidence no longer changes, assume there are n pieces of evidence similar to m3. To show the use of the proposed combination rule as n changes. The five pieces of evidence collected by the system are as follows: (n=3)

S1:$(\mathcal{R}_1, m_1) = \quad ([\{A\}, 0.98], [\{B\}, 0.01], [\{C\}, 0.01])$

S2:$(\mathcal{R}_2, m_2) = \quad ([\{A\}, 0.01], [\{B\}, 0.98], [\{C\}, 0.01])$

S3:$(\mathcal{R}_3, m_3) = \quad ([\{A\}, 1/3], [\{B\}, 1/3], [\{C\}, 1/3])$

S4:$(\mathcal{R}_4, m_4) = \quad ([\{A\}, 1/3], [\{B\}, 1/3], [\{C\}, 1/3])$

S5:$(\mathcal{R}_5, m_5) = \quad ([\{A\}, 1/3], [\{B\}, 1/3], [\{C\}, 1/3])$

Where n is the same amount of evidence as to the last three sets of evidence.

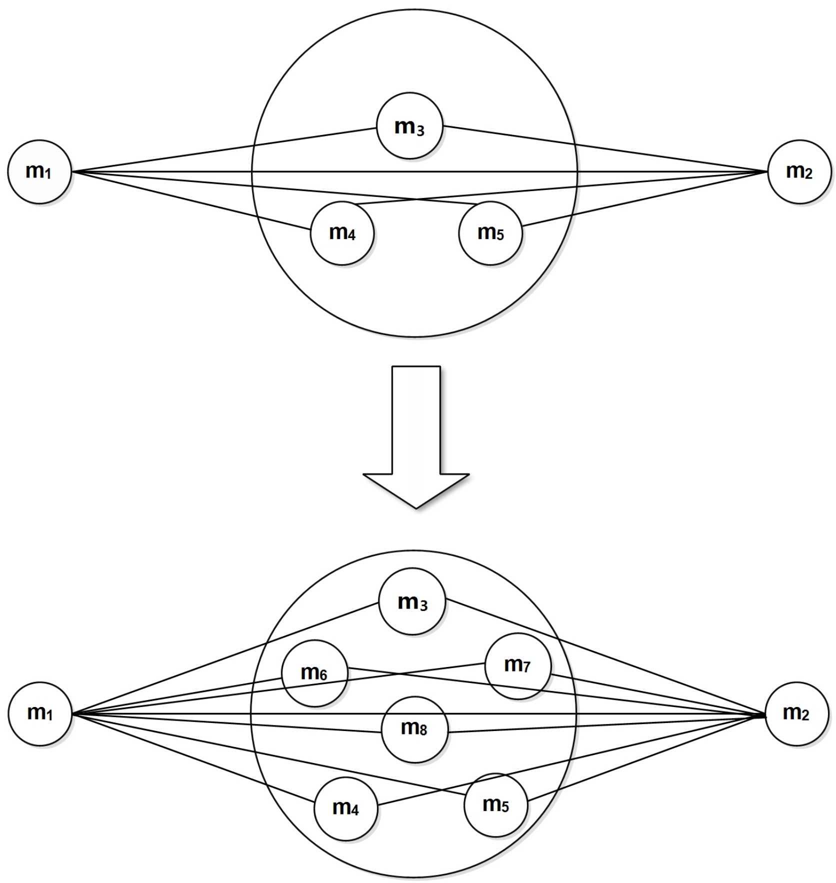

Figure 14. The amount of credible evidence change diagram.

The final weight obtained for each piece of evidence is shown in the figure below(Take five pieces of evidence and nine pieces of evidence as examples):

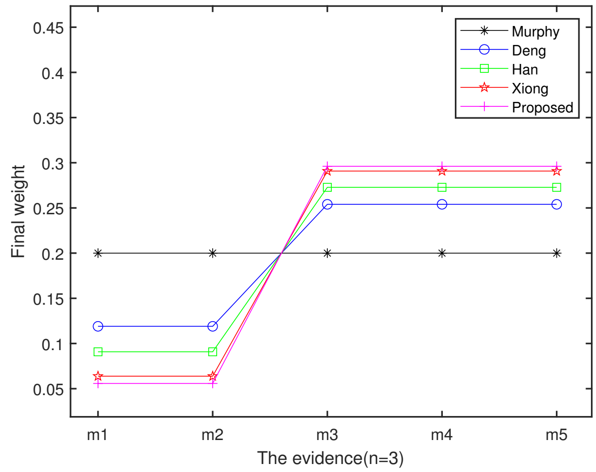

Figure 15. The final weight of each piece of evidence.

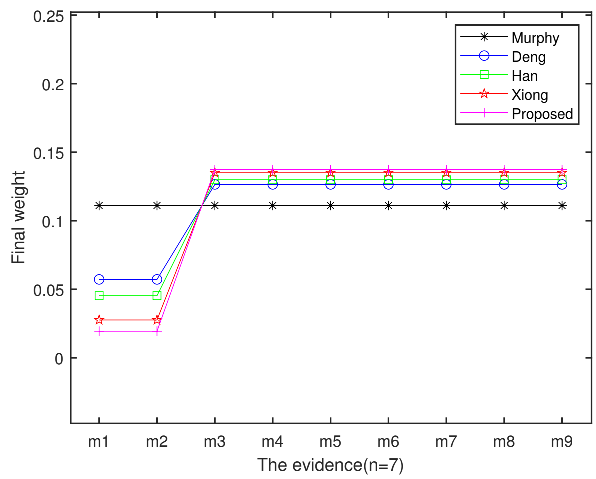

Figure 16. The final weight of each piece of evidence.

The final result is shown in the table below: (m1,m2,m3,m4,m5)

Table 6: Results of different combination rules of evidence

Approach	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$
Dempster combination rule[9, 10]	m(A)=0.4975 m(B)=0.4975 m(C)=0.0050	m(A)=0.4975 m(B)=0.4975 m(C)=0.0050	m(A)=0.4975 m(B)=0.4975 m(C)=0.0050	m(A)=0.4975 m(B)=0.4975 m(C)=0.0050	m(A)=0.4975 m(B)=0.4975 m(C)=0.0050
Murphy's method[30]	m(A)=0.4913 m(B)=0.4913 m(C)=0.0174	m(A)=0.4904 m(B)=0.4904 m(C)=0.0192	m(A)=0.4898 m(B)=0.4898 m(C)=0.0204	m(A)=0.4894 m(B)=0.4894 m(C)=0.0212	m(A)=0.4891 m(B)=0.4891 m(C)=0.0218
Deng's method[31]	m(A)=0.4639 m(B)=0.4639 m(C)=0.0723	m(A)=0.4591 m(B)=0.4591 m(C)=0.0817	m(A)=0.4559 m(B)=0.4559 m(C)=0.0882	m(A)=0.4536 m(B)=0.4536 m(C)=0.0929	m(A)=0.4518 m(B)=0.4518 m(C)=0.0964
Han's method[32]	m(A)=0.4447 m(B)=0.4447 m(C)=0.1107	m(A)=0.4399 m(B)=0.4399 m(C)=0.1201	m(A)=0.4375 m(B)=0.4375 m(C)=0.1250	m(A)=0.4361 m(B)=0.4361 m(C)=0.1277	m(A)=0.4354 m(B)=0.4354 m(C)=0.1293
Xiong's method[33]	m(A)=0.4197 m(B)=0.4197 m(C)=0.1606	m(A)=0.4128 m(B)=0.4128 m(C)=0.1745	m(A)=0.4083 m(B)=0.4083 m(C)=0.1833	m(A)=0.4053 m(B)=0.4053 m(C)=0.1894	m(A)=0.4031 m(B)=0.4031 m(C)=0.1938
Proposed method	m(A)=0.4110 m(B)=0.4110 m(C)=0.1781	m(A)=0.3988 m(B)=0.3988 m(C)=0.2025	m(A)=0.3920 m(B)=0.3920 m(C)=0.2160	m(A)=0.3878 m(B)=0.3878 m(C)=0.2245	m(A)=0.3848 m(B)=0.3848 m(C)=0.2304

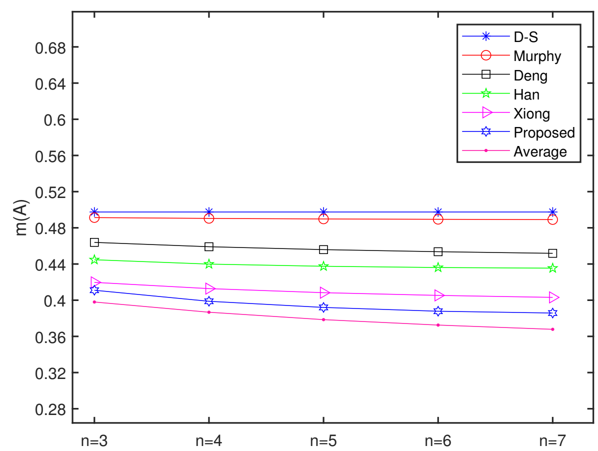

Figure 17. Convergence effect of m(A) in the composite result

From Table 6 and Figure 17, we can see that as n increases, the results continue to move closer to average value. The results of our proposed method are closest to the final results. From Figure 15 and Figure 16, the larger the n, the stronger we weaken the conflict evidence and credible evidence gets more weight. This shows that though the change in the quantity between conflict evidence and credible evidence, our method is still effective.

5.3. Superiority of the proposed method

Compared to other methods, this paper mainly considers the influence of the data on the final result through the variance of the support degree between the evidence. And the method can get a reasonable result. In a set of evidence, we always think that reliable evidence is the majority, so the evidence are closer together and easier to aggregate together. When a piece of evidence's support degree value is small, it will be far away from reliable evidence, that is, conflict evidence. The method proposed in this paper is used to weaken such conflict evidence, to make the final result more reasonable. Comparing with previous methods through classic examples, our results are more effective. This shows that our method is available. Whether it is a change in the degree of conflict or a change in the amount of credible evidence, the proposed method can enhance to weaken the influence of the conflict evidence. This also shows that in most cases, our method is still effective.

6. Conclusion

In the process of evidence fusion, the existence of conflict evidence will lead to deviations in the results. Since conflict evidence cannot be determined, we can only find ways to weaken the impact of conflict evidence on the final results. Therefore, based on the contribution of the Murphy and Deng, this paper mainly considers the influence of the variance of the support degree between the evidence on the final results. By adjusting the weight of each piece of evidence, the final results have a more effective result. The examples show the effectiveness and better performance of convergence.

The main contributions of the proposed method are: (1)Compared with previous methods, choose classic evidence examples for fusion. The results of the following numerical examples show that our proposed method can manage conflict evidence better than existing work. (2)The change in the degree of conflict will not affect the use of our methods. (3)The change in the amount of credible evidence shows the effectiveness of our method. The final results show that our method can still obtain a reasonable result.

In subsequent research, perhaps this method can be applied to decision-making under strong uncertainty in the framework of Dempster-Shafer theory, such as group decision-making in autonomous robot systems, multi-agent systems, and so on. Of course, if there is much unreliable evidence in a set of evidence, the results obtained by this method will also be counter-intuitive.

Conflict of interest

The authors declare that they have no conflict of interest.

Acknowledgment

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