A Weighted Evidence Combination Method Based on Improved Conflict Measure Factor

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Abstract

D-S evidence theory is usually used for the fusion of multi-source information. But the fusion result is always against with general knowledge for the heavy conflict of evidence. Research on combination of conflict evidence at home and abroad is summarized and analyzed in detail. On the base of this, the conclusion that modified evidence combination method of conflict evidence is more useful can be dawn. Effective evidence conflict measure is the first step of conflict evidence combination. The existing conflict measure methods are summarized and the main problem of those methods is analyzed in detail. Based on previous research of conflict evidence combination, a modified measure factor of evidence conflict which is called Mconf is put forward. Mconf is mainly built up with modified distance of evidence named md_{BPA} and traditional evidence conflict factor named k. The examples in this paper show that Mconf can measure the evidence conflict correctly, both for general evidence and conflict evidence.

Keywords: conflict evidence combination, conflict measure, modified evidence distance, traditional conflict factor, improved conflict factor

1. Introduction

Due to the differences of knowledge acquisition approaches and the measuring error of the system and the sensor, there are redundancies and contradictories in multiple sources. Dempster-Shafer theory is an effective method to fuse uncertainties of conflict information. It is significant effect using D-S evidence theory to solve the uncertain problems because of the lack of knowledge. With the intemsive study of D-S evidence theory, it's found that there are perverse conclusions when fusing multi-source based on the D-S evidence theory [1]. Aiming at this problem, researchers have conducted in depth research both at home and abroad, and put forward some solutions. The peper will condut a detailed analysis. Based on the criticism of predecessors' research results, an improved conflict measure factor Mconf based on correction distance md_{BPA} and conflict factor k is put forward. The conflict between evidences is measured based on md_{BPA} and the weight value of each evidence is calculated. The evidence is modified and the final decision can be obtained based on the modified evidence.

2. Induction of Conflict Evidence Fusion

Aiming at the fusion of conflict evidence, it can be roughly divided into two groups. The first group is modified combination rule method, another group is to revise the evidences.

2.1. The Modified Combination Rule Method

The method of modifying and revising rues considers that the appearance of counter-intuitive result is due to the use of disposable approach in handling evidence conflict based on Dempster combination rule. There are some typical examples such as Yager rule, Smets rule, DP rule, Sun Quan rule, PCR5 rule proposed by Smarandache and Desert.

Evidence conflicts were classified into global X what is completely unknown through Yager rule [2]. It can solve the problem of fusion of two highly conflicting evidences. The low supporting evidence still supports low after fusion through such treatment. And the conflict evidence is completely abandoned by such treatment. Therefore, even if there are multiple evidences strongly supporting the focal element of the previous conflict evidence. The final

fusion result is entirely negative and irrational. Smets rule would classify section conflict to the empty set, consistent with the Yager rule's problem [3]. DP rule assigns the BPA of conflict evidence to union set of the conflict focal element [4]. It is suitable for strong conflict evidence, while it always seems conservative and the convergene is slow. Sun Quan rule considers conflict evidence is still available whose degree of the available is depended on credibility ε defined by Sun Quan rule [5]. When dealing with high conflict evidence, PCR5 rule has a certain advantage. While dealing with general non-conflict evidence, the fusing effect is bader than traditional Dempster rule's convergence and PCR5 rule is not associative [6-7].

2.2. The of Revising Evidence Method

Amend evidence method considers Dempster combination rule is right. The appearance of paradox is due to the error of evidence. Evidence should be modified before combination, then the conclusion is more reasonanle in the aspects of physics, mathematics and logic. There are typical examples such as Murphy average evidence method, Deng yong expectation evidence method, Yeqing weighte evidence method, Liu Zhunga relative weighting evidence method, Yin xuezhong weighted evidence method, Liuweiru conflict combination recognition method, Liu Zhunga integrated weighted evidence method and Li bo integrated weighted evidence method.

Murphy made the mass of corresponding to the focal element of all the evidence sharing [8]. Then composite n-1 evidences based on Dempster rule. The method deems each evidence equal weight. While each source of information has different reliabilities, or the sensors may have failure in practical problems, so each evidence should have different weight.

Deng yong computed Jousselme distance between two evidences in order to obtain distance matrix DM [9]. Evidence similarity matrix SM was defined 1-DM. Then obtain all evidence weights based on similarity matrix. The evidences are given different weights and then sum all of them. Combine the modified evidences 'n-1' times based on Dempster rule.

Ye Qing calculate conflict factor between two evidences to generate conflict matrix K [10]. K was normalized and takes entropy to generate evidence weight coefficients. Modify the evidence based on the weight factor. Composite the revised evidence based on Sunquan rule.

Liu Zhunga calculated credibility as a weight value based on Deng Yong's paper. Make the maximum weight value corresponding evidence as standard evidence, and the standard evidence is not to be processed [7]. The remaining evidences are modified in accordance with weights comparing with standard evidence. The surplus mass value of amendable evidence was assigned to full set of each evidence. Combine the modified evidences based on Dempster rule.

Yin Xuezhong calculate each weight value based on Liu Zhunga [11]. Do not select standard evidence, while all evidences will be revised. Combine the evidence based on Dempster rule.

Liu WeiRu proposed sectional conflict measure based on gambing promises distance difBetP and conflict factor k [12]. It mainly adopts the method of threshold determination. Do not operate anything with difBetP and k. Assign a value for the conflict threshold ε according to the practical application. If and only if the value of difBetP and k are lagrer than or equal to ε value, there is a serious conflict between evidences. In the rest conditions, combine evidence based on Dempster rule. Liu WeiRu just put forward a kind of composite measure of evidence conflict based on difBetP and k. But it did not give a solution when the conflict is large.

The conflict of evidence can't be measured properly based on evidence distance or conflict factor k only. Liu Zhunga put forward the two's geometric mean $\sqrt{k \cdot d_{BPA}}$ to represent conflict between evidences [13]. Revise the evidences after calculating each evidence weights. Composite the revised evidences with expectations evidence method and relative weighting evidence method.

Li Bo pointed out that using $\sqrt{k \cdot d_{BPA}}$ to measure the degree of conflict between evidences, when the difference of the evidence is small, the conflict measure value based on $\sqrt{k \cdot d_{BPA}}$ grow too fast compared with $k \cdot d_{BPA}$. And it is easy to cause error calculation. But when the value of n of conflict measure factor takes too much, the conflict measure factor will be not sensitive to the change of evidence in a certain range. So, Li Bo took $k \cdot d_{BPA}$ as conflict measure factor [14].

2.3. Comprehensive Evaluation of Two Methods

Dempster rule have some good mathematical properties, such as commutative law and associative law. Modify the combination rules usually destroy the mathematical properties. When the combination rule can not satisfy the associative law, multiple evidence fusion order is bound to affect the fusion result. If combining all the evidence together, the calculation will be exploding. In fact, aiming at the problem of health monitoring of complex system, when the sensor breaks down or or there is a transmission error, strong conflict evidence will come out. It is irrational that to make the problem to combination rule [15]. Therefore it is more reasonable to combine conflict evidence based on revising evidence method.

3. Measure on Evidence Conflict

It's required that evidences be mutually independent when Dempster combination rules is applied to the combination of multi-source evidence, so evidences are independent of each other by default. The rule that the minority is subordinate to the majority is applied to Troubleshooting evidence, that is to say, if one evidence is rejected by others, it is very likely to be fault evidence, and its intensity should be weakened during evidence combination. The degree of opposition among evidence is called evidence conflict, so conflict between evidence should be measured.

3.1. Current Method for the Measure of Conflict

Currently, there are 2 kinds of method to measure the conflict of evidence: one of them is the conflict factor k proposed by Dempster and Shafer; the other is the confidence level, which is based on Jousselme distance calculation. Originally, Jousselme distance is used for the calculation of the difference between the decision by evidence combination and the reality. Then it is used to measure the conflict between the evidences. It is pointed that a single method of the two can't measure the conflict exactly in paper [12] and [14]. Therefore, some researchers proposed that the decision be based on k and d in the form of the two.

3.2. The Main Problem

Peng proposed that, Jousselme distance is insufficient when it is applied to measure the general evidence conflict. The bigger BPA degree of dispersion is, the smaller the Jousselme distance of two evidence. In fact, each group of evidence is completely conflicted. As for 2 groups of category evidence, it is totally conflicted among evidences but the Jousselme distance is not the max value 1. The reason is that when it is normalized, the denominator is const value 2, and it can't extend. Hence, amendment evidence distance md_{BPA} is proposed. On the basis of excellent character retention, all the problems are solved and the stypticity is better. Therefore, amendment evidence distance md_{BPA} and k is combined to measure evidence conflict in this paper [16].

The definition of amendment evidence distance md_{BPA} is as formula (1) and (2):

$$md_{\mathrm{BPA}} = \sqrt{\frac{\langle m_1, m_1 \rangle + \langle m_2, m_2 \rangle - 2\langle m_1, m_2 \rangle}{\langle m_1, m_1 \rangle + \langle m_2, m_2 \rangle}} \tag{1}$$

$$\langle \boldsymbol{m}_1, \boldsymbol{m}_2 \rangle = \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \boldsymbol{m}_1(A_i) \cdot \boldsymbol{m}_2(B_j) \cdot \frac{A_i \cap B_j}{A_i \cup B_j} \tag{2}$$

The product of k and d_{BPA} is used in both paper [13] and [14] to measure the evidence conflict, and the unique difference is the value of n in $(k \cdot d_{\mathrm{BPA}})^n$. It is pointed in paper [13] that when the BPA value changes, k and d_{BPA} have no direct correlation. If the product rule for the parameter md_{BPA} and k is applied by the thought of paper [13] and [14], the evidence conflict can't be measured exactly. The reason is that once a parameter is 0, 2 evidences are decided not conflicted no matter the other parameter is. However, facts are not all so. As is indicated in example 1.

Ex 1 Suppose frame of discernment is $X = \{\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6\}$, the BPA of 2 evidences are:

case1: $m_1(\theta_1, \theta_2, \theta_3, \theta_4) = 1$; $m_2(\theta_4, \theta_5) = 0.8$ $m_2(\theta_3, \theta_6) = 0.2$

case 2: $m_1(\theta_i) = m_2(\theta_i) = 0.2, i = 1, 2, \cdots, 5$

case 3: $m_1(\theta_1, \theta_2) = a$ $m_1(\theta_2, \theta_3) = 1 - a, a \in [0,1]$; $m_2 = m_1$

case 4: $m_1(\theta_1) = 0.99$ $m_1(\theta_2) = 0.01$

$\quad\quad m_2(\theta_1, \theta_2) = 0.01$ $m_2(\theta_1, \theta_2, \theta_3) = 0.99$

$\quad\quad m_3(\theta_1) = 0.9$ $m_3(\theta_2) = 0.1$

case 5: $m_1(\theta_i) = 1/6, i = 1, 2, \cdots, 6$; $m_k(X) = 1, k = 2, 3, \cdots, m$

case 6: $m_1(\theta_1) = 0.9$ $m_1(\theta_2) = 0.1$; $m_1(\theta_1) = 0.1$ $m_1(\theta_2) = 0.9$

The values of traditional conflict factor k、amendment evidence distance md_{BPA} and $md_{BPA} \cdot k$ in the cases of example 1 are indicated in Table 1.

Table 1. The values of k and md_{BPA} and $md_{BPA} \cdot k$ of example 1

Case		md_{BPA}	k	$md_{BPA} \cdot k$	$(k + md_{BPA})/2$
Case 1	m_1与m_2	0.8729	0	0	0.4365
Case 2	m_1与m_2	0	0.8	0	0
Case 3	m_1与m_2	0	0	0	0
	m_1与m_2	0.8127	0	0	0.4064
Case 4	m_1与m_3	0.0949	0.1080	0.0102	0.1015
	m_2与m_3	0.7914	0	0	0.3957
Case 5	m_1与m_k	0.8452	0	0	0.4226
Case 6	m_1与m_2	0.8835	0.82	0.7245	0.8518

It can be concluded from the analysis of example 1:

In case 1, evidence m_1 and m_2 are in conflict, $md_{BPA} \cdot k$ misjudges evidence as 0.

In case 2 and 3, evidence m_1 and m_2 are identical, and there is no conflict between the evidences. No matter what the value 'a' is, the value of md_{BPA} is always 0, so $md_{BPA} \cdot k$ can judge evidences in conflict.

In case 4, evidence m_1 and m_3 are significantly in support of θ_1 , and m_2 judges that the possible conclusion may be included in $(\theta_1, \theta_2, \theta_3)$ with the possibility of 99%. By analysis, the conflict between m_1 and m_3 is smaller than that between m_1 and m_2。 But in fact, the conflict value between m_1 and m_2 is 0, which is smaller than that of m_1 and m_3. So it is contrary to analysis. What's more, the conflict degree between m_1 and m_2 are evidently different from that between m_2 and m_3. It is concluded that there is no conflict between 2 groups of evidences by conflict measurement of $md_{BPA} \cdot k$ and that the judgement is wrong.

In case 5, evidence m_1 indicates that all the elements in identification frame can't be assured. Evidence m_k indicates that identification is totally unknown. Evidently, they are not equal, ie, there is conflict among evidences. When conflict measurement of $md_{BPA} \cdot k$ is applied, it is concluded that there is no conflict between 2 groups of evidences, which is wrong.

In case 6, obviously, there is conflict between evidence m_1 and m_2. Value $md_{BPA} \cdot k$ is big and the judgement is right.

On the basis of the above analysis, the following conclusions can be drawn:

(1) As case 2 in example 1, when 2 evidences are identical, there is no conflict;

(2) As case 1 and case 3 in example1, when there is intersection in all the focal elements of the 2 evidences(intersection is not Φ), the traditional conflict factor k is always 0, the amendment evidence distance md_{BPA} value is not always 0. In this case, there must not be conflice between evidences, but $md_{BPA} \cdot k$ value is always 0 by the effect of k, which is not correct.

(3) As case 4 in example 1, in the situation where there are many (take 3 as example) source-evidence, if all the focal elements among 2 different evidences and the third evidence

have intersection, conflict fator k is 0. But the 2 evidences are not equal to the third. So the method with $md_{BPA} \cdot k$ is not correct.

(4) As case 5 in example 1, when there is evidence as "$m(X) = 1$", other evidences have no conflict with it, and method by $md_{BPA} \cdot k$ is not correct.

3.3. Improvement of Conflict Measure Method

Combine the analysis in 3.2 and the achievement by predecessors, it is proposed a novel evidence conflict measure factor Mconf, it is expressed as formula (3):

$$\text{Mconf} = \begin{cases} 0 & md_{BPA} = 0 \\ \dfrac{k + md_{BPA}}{2} & md_{BPA} \neq 0 \end{cases} \qquad (3)$$

From formula (3), it can be concluded that Mconf depends on traditional conflict fator k and amendment evidence distance md_{BPA}. There are two cases. First, when evidences are idetical, there is no conflict and conflict value is 0; second, when evidences are not identical, take them as equal and sum the weights regardless of product of md_{BPA} and k in paper [13] and [14]. To guarantee the value of Mconf between [0,1], normalization is needed. As k and md_{BPA} is between 0 and 1, the denominator is 2.

Once the novel conflict measure factor Mconf is applied to measure the conflict between the evidence, there are characters as follows:

(1) $\text{Mconf}(m_1, m_2) \in [0,1]$;

(2) $\text{Mconf}(m_1, m_2) = 0$, if and only if $m_1 = m_2$;

(3) $\text{Mconf}(m_1, m_2) = 1$, if and only if $(\cup A_i) \cap (\cup B_j) = \Phi$, A_i 和B_j are focal elements of m_1 and m_2 ;

The certification of the characters above is easy and it is introduced simply in this paper. As k and md_{BPA} is between 0 and 1, (1) is certificated. If and only if $m_1 = m_2$, md_{BPA} is 0, character (2) is certificate. If and only if k and md_{BPA} are 1, $\text{Mconf}(m_1, m_2) = 1$, then it can be concluded $(\cup A_i) \cap (\cup B_j) = \Phi$, and the opposite is true. So character (3) is certificate.

In actual application, when the novel conflict measure factor Mconf is applied to measure the conflict between the evidence, a threshold value ε should be set with actual situation. It can be identified that there is big conflict only when k and md_{BPA} are big. Threshold value ε is set as 0.7.

Measure the conflict in the situations like example 1, it can be concluded:

As case 1 in example 1, evidence m_1 and m_2 are small, $\text{Mconf}(m_1, m_2)$ =0.4365, so judgement is right.

AS case 2 and case 3 in example 1, m_1 and m_2 are identical, and there is no conflict, $\text{Mconf}(m_1, m_2)$ =0, and the judgement is correct.

As case 4 in example 1, conflict among m_1 and m_2、m_2 and m_3、m_1 and m_3 are small. $\text{Mconf}(m_1, m_2)$ =0.4064, $\text{Mconf}(m_2, m_3)$ =0.3957, $\text{Mconf}(m_1, m_3)$ =0.1015, judgement is right.

As case 5 in example 1, whatever k is, conflict between m_1 and m_k are small, i.e., any evidence is not in conflict with $m(X) = 1$, $\text{Mconf}(m_1, m_k)$ =0.4226, judgement is correct.

As case 6 in example 1, there is a big conflict between m_1 and m_2, $\text{Mconf}(m_1, m_2)$ =0.8518, and the judgement is correct.

In conclusion, the novel conflict measure factor Mconf can measure the conflict among evidence.

4. Weighted Evidence Combination based on Mconf
4.1. Algorithm Design

Assuming the identification framework $X = \{\theta_1, \theta_2, \cdots, \theta_m\}$, and the number of evidence is n. Weighted evidence combination algorithm based on Mconf is designed as follows:

a) See all the evidences as a group, the conflict of one evidence from the other one, which two are both from the group, is calculated based on Mconf. And the conflict of every two evidences in the group should be done. $\text{Mconf}_{i,j}$ is shown as formula (4).

$$\text{Mconf}_{i,j} = \frac{k_{i,j} + md_{\text{BPA}_{i,j}}}{2} \qquad i, j = 1, 2, \cdots, n \tag{4}$$

b) Evidence conflict matrix is constructed by $\text{Mconf}_{i,j}$, and the order of matrix is $n \times n$. **Conf** is shown as formula (5).

$$\mathbf{Conf} = \begin{bmatrix} 0 & \text{conf}_{1,2} & \cdots & \text{conf}_{1,n} \\ \text{conf}_{2,1} & 0 & \cdots & \text{conf}_{2,n} \\ \vdots & \vdots & 0 & \vdots \\ \text{conf}_{n,1} & \text{conf}_{n,2} & \cdots & 0 \end{bmatrix}_{n \times n} \tag{5}$$

c) The conflict summation of evidence *i* and all the other evidence from the group is calculated based on **Conf**(*i*), and **Conf**(*i*) is shown as formula (6).

$$\mathbf{Conf}\,(i) = \sum_{j=1, j \neq i}^{n} \text{conf}_{i,j} \tag{6}$$

d) The support degree of evidence *i* which is supported by the other evidences from the group can be drawn as $u(i)$ which is shown as formula (7).

$$u(i) = 1 - \mathbf{Conf}\,(i) / \sum_{i=1}^{n} \mathbf{Conf}\,(i) \tag{7}$$

e) The weight value of evidence *i* can be drawn as $\alpha(i)$, which is shown as formula (8).

$$\alpha(i) = u(i) / \sum_{i=1}^{n} u(i) \tag{8}$$

f) The two evidences from the group should be independent when use Dempster combination rule. The modified evidence in paper [13] and [14] has a significant correlation obviously because of its generating method. So Dempster combination rule can't be used in this situation [17]. In this paper, the combination evidence m_{comb} can be drawn from the weighted evidence combination of all the evidence in the group, and m_{comb} is shown as formula (9).

$$m_{\text{comb}} = \sum_{i=1}^{n} \alpha(i) \cdot m_i \tag{9}$$

g) Assumed that the number of focal elements in evidence in m_{comb} is *k*, and the focal elements of m_{comb} can be called A_k. The final evidence m_{final} which is shown as formula (10) can be drawn from m_{comb} [18].

$$m_{\text{final}}(\theta_l) = \sum_{\theta_l \in A_k, A_k \subset 2^X} \frac{1}{|A_k|} \cdot m_{\text{comb}}(A_k) \qquad l = 1, 2, \cdots, m \tag{10}$$

4.2. Verification of Typical Case

In order to make a good comparison, the example in paper [14] is selected for validation. Assuming the identification framework $X = \{\theta_1, \theta_2, \theta_3, \theta_4\}$, and the number of evidences is 6. The typical case contains two situations. In situation 1, the sensor is normal, and the conflict between evidences is small. In situation 2, the sensor is failure, and the conflict between evidences is large.

Situation 1: The system and the sensor are both normal, and BPA of every evidence is shown as follows:

$$m_1(\theta_2, \theta_3, \theta_4) = 0.9, m_1(X) = 0.1 \; ; \; m_2(\theta_1, \theta_2) = 0.1, m_1(\theta_3, \theta_4) = 0.9$$
$$m_3(\theta_1, \theta_2) = 0.2, m_3(\theta_3, \theta_4) = 0.8 \; ; \; m_4(\theta_1, \theta_2, \theta_3) = 0.95, m_1(X) = 0.5$$
$$m_5(\theta_4) = 0.6, m_5(\theta_2, \theta_3, \theta_4) = 0.4 \; ; \; m_6(\theta_1, \theta_3, \theta_4) = 0.75, m_6(X) = 0.25$$

The combination result of evidences in situation 1 based on the proposed algorithm in this paper is shown as table 2. And the result can be compared with the algorithms in paper [14].

Table 2. The combination result in situation 1

Number	Combination rules	BPA of evidence after combination	Weight values
1	D-S combination rule	$m(\theta_2) = 0.0028$ $m(\theta_4) = 0.9773$ $m(\theta_3, \theta_4) = 0.0199$	Null
2	Murphy average evidence algorithm[8]	$m(\theta_4) = 0.8296$ $m(\theta_3, \theta_4) = 0.1465$	[0.1667, 0.1667, 0.1667 0.1667, 0.1667, 0.1667]
3	Liu ZhunGa comprehensive weighted evidence algorithm[13]	$m(\theta_4) = 0.9771$ $m(\theta_3, \theta_4) = 0.0222$	[0.62, 0.99, 1.00 0.99, 1.00, 1.00]
4	Li Bo comprehensive weighted evidence algorithm[14]	$m(\theta_4) = 0.9771$ $m(\theta_3, \theta_4) = 0.0200$	[1.00, 1.00, 1.00 1.00, 1.00, 1.00]
5	Algorithm in this paper	$m(\theta_1) = 0.1350$ $m(\theta_2) = 0.1657$ $m(\theta_3) = 0.2745$ $m(\theta_4) = \mathbf{0.4248}$	[0.1687, 0.1685, 0.1688 0.1613, 0.1652, 0.1674]

Situation 2: The system is normal, and evidence m_1 is different from it in situation 2 because of the sensor failure, the other evidence have no change. The changed BPA of evidence m_1 is shown as follows:

$$m_1(\theta_1) = 0.9, m_1(\theta_1, \theta_3) = 0.1$$

The combination result of evidences in situation 2 based on the proposed algorithm in this paper is shown as table 3. And the result also can be compared with the algorithms in paper [14].

From typical case of situation 1 and situation 2, we can conclude that no matter the sensor is in failure or not, the proposed algorithm in this paper can make a decision correctly. When there is a sensor failure, the fault evidence can be clearly identified based on the weight values of initial evidences. And the negative effects brought by the fault evidence can be eliminated to maximize. Then the final correct decision is concluded.

Table 3. The combination result in situation 1

Number	Combination rules	BPA of evidence after combination	Weight values
1	D-S combination rule	$m(\theta_1) = 1.0000$	Null
2	Murphy average evidence algorithm[8]	$m(\theta_1) = 0.0994$ $m(\theta_4) = 0.7949$	[0.1667, 0.1667, 0.1667 1667, 0.1667, 0.1667]
3	Liu ZhunGa comprehensive weighted evidence algorithm[13]	$m(\theta_4) = 0.8868$ $m(\theta_3, \theta_4) = 0.0250$ $m(\theta_1, \theta_4) = 0.0124$	[0.49, 0.76, 0.77 1.00, 0.73, 1.00]
4	Li Bo comprehensive weighted evidence algorithm[14]	$m(\theta_4) = 0.9729$ $m(\theta_3, \theta_4) = 0.0201$	[0.63, 0.99, 1.00 1.00, 0.99, 1.00]
5	Algorithm in this paper	$m(\theta_1) = 0.2775$ $m(\theta_2) = 0.1151$ $m(\theta_3) = 0.2306$ $m(\theta_4) = \mathbf{0.3768}$	[**0.1478**, 0.1690, 0.1701 0.1720, 0.1651, 0.1760]

5. Conclusion

In this paper, research on combination of conflict evidence at home and abroad is summarized and analyzed in detail. And we conclude that effective evidence conflict measure is the first step of conflict evidence combination. There are some problems in existing conflict measure methods, so a new conflict measure factor Mconf is proposed based on previous research. The case show that Mconf can measure evidence conflict correctly. A weighted evidence combination algorithm based on Mconf is designed, and the typical case show that the proposed algorithm can complete the evidence combination effectively, both for general evidence and conflict evidence.

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