A Multi-source Information Fusion Method of Non-identical Evidence Conflicts

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Abstract
Since evidence conflict of high degree has been the main problem of restricting D-S evidence information fusion, this paper starting from the definition and description of conflict evidence, analyzes the nature of evidence conflict combined with the sort of information; according to the definition of evidence uncertainty degree and the correlation between measurement, the new connotation of evidence conflict resulted from the internal and external contradictions is put forward; based on the binary measure, a conflict identification method based on evidence uncertainty is proposed. By simulation and verification, it makes a conclusion: the method achieves the effectiveness of a variety of measurements when the evidence conflict is identical; it solves the universality of measurement when the measurement shows difference; and through the uncertainty degree empowerment, it ensures the identification capability and accuracy of high-degree evidence conflicts.
Key words: EVIDENCE CONFLICT, MEASUREMENT, INFORMATION DISTANCE, UNCERTAINTY, IDENTIFICATION.

1. Introduction

Multi-source information fusion provides more reliable mechanism safeguard for decision-making and forecast system, and the relatively complex information processing and feature recognition also put forward higher technical requirements in terms of fusion method. The purpose of fusion is to make the uncertainty of various information in consistency, and provide the decision information support of "uncertainty" value for system. On the basis of assumption that information is reliable, Dempster-Shafer makes update for evidence trust, and optimize information synthesis with mutual support and complementary advantages among the multi-evidences. It is now recognized as one of the commonly used method of dealing with uncertain information. Due to the reliability of information itself and the environment influence in the practical application, different levels of conflict (information is different) exists among evidences. Therefore, the synthesis constraint problems occur to D-S evidence theory when differences exist in evidence support of high-degree conflict and the evidence conflict under different measurement.

In terms of the D - S evidence synthesis problem of high-degree evidence conflict, as early as 1984, Zadeh [1] pointed out that the synthetic resulted of highly conflict evidence might appear contrary to actual convention by introducing typical cases. Since then, Zhang Suodi etc. [2] constructed three paradoxes which provide the application area for synthetic rules of D-S theory. At present, D - S evidence synthesis research is mainly concentrated in two aspects: one is measuring and identifying problems of high-degree evidence conflict; the other is fusion processing problems after evidence conflict identification. In the measurement of evidence conflict, according to D - S rules, normalizing factor k is used to modify synthetic information, and it is nominated to be conventional conflict coefficient in this paper. Yang Jianping [3] constructed two different evidences, and conflict $k=0$ reflects the incompleteness of traditional conflict coefficient. Therefore, Martin [4] by Jousslme information distance, Hu Changhua [5] by defining the game reliability distance, Li , et al [6] using k - L information distance make measurement of evidence conflict from the perspective of information difference respectively. Jiang Wen, etc. [7-10] holds that Θ only describes the non-intersection degree between the focal elements and cannot fully reflect the evidence conflict. So they put forward binary measurement method which combining the conflict coefficient with gambling distance, Jousslme distance, vector distance and so on. The existing binary measure makes a more comprehensive description for evidence conflict from the different angles of view. When conflicts are consistent under different measurement, the method is the most effective, but for the handling of the conflict, it is often based on the data itself and cannot give the reasonable explanation of the evidence essence. Concerning the issues of conflict evidence fusion, Haenni [11] considers that the typical counter- example given by Zadeh is only to illustrate the application D - S synthesis exist constraints rather than the mistakes of rule itself. Therefore, a reasonable determination for the range of constraints and appropriate fusion method outside the scope are needed. Smets [12] considers that the incompleteness of evidence identification framework is the reason of causing conflict, thus, allocating conflict reliability to the empty set could improve convergence. This processing of conflict information transiting from "not sure" to "I don't know" runs counters to the system of "ok" goal. Based on the evidence conflict absorption, Liang Changyong, etc. [13] presents a synthesis method which transmits conflict caused by evidence with same basic probability to supporting reliability of evidence, thus eliminating the paradox and convergence. This method transiting the information directly to the "ok" greatly improves the decision-making risk of the high-degree conflict. The above evidence synthesis methods are all based on evidence conflict consistency, and distribute non-uniform conflict to "unknown" or "known". These treatments without combining conflict inconsistence with evidence essences are likely to cause the loss of important information, thus causing false alarm of the system.

This paper, starting from the basic theory of D - S evidence, presents two cases under different measurements, conflict characterization consistence and conflict characterization inconsistence. It analyzes the cause of the inconsistent conflict, explains the essence of the conflict evidence by introducing evidence uncertainty, and puts forward a non-uniform evidence conflict identification method based on the uncertainty. After making isolation analysis of high-degree conflict evidence identified, D - S fusion is made. And through the comparison with DSmT fusion method which is able to solve the high-degree contradiction information, the effectiveness of this paper can be checked through analysis.

2. D-S Evidence Theory

D-S theory assumes a nonempty set Θ, used to describe all elements of mutual exclusion and exhaustion, and $\Theta=\{A_1, A_2 \cdots, A_N\}$ is called recognition framework. A collection with the element being N, includes 2^N mutex subsets, is marked as 2^Θ. In D-S theory, Mass is represented by the degree of belief in support of proposition.

According to **definition 1**[1] assume set Θ as the recognition frame of D-S theory, the complete and mutually exclusive proposition composing power set function $m: 2^\Theta \to [0,1]$, and satisfying

$$m(\phi)=0, \sum_{A\subset\Theta} m(A)=1$$

Then, m (A) is called the BPA of A under the frame of Θ, denoting the evidence degree of trust and support for A. When $m(A)\neq 0$, then A is called the focal element (namely, evidence's focus on A) of BPA.

Assume the BPA assignment function of evidence M1, M2 in the same recognition frame is m_1, m_2, and the focal element is $(A_1,\cdots,A_k)$, $B_1,\cdots,B_l)$, then the evidence fusion result is:

$$m(C) = m_1 \oplus m_2 = m_1(A) + m_2(B)$$
$$= \frac{1}{1\text{-}K} \sum_{A_{i1} \cap B_{j2} = C} m_1(A_i) m_2(B_j) \qquad \forall C \subset \Theta, C \neq \varphi \tag{1}$$

Here, $m(C)$ is new evidence assignment produced after orthogonal combination of m1, m2; $C = A_{i1} \cap B_{i2}$, namely, when $A_{i1} \subseteq B_{j2}$, $C_i = A_{i1}$, which represents the same information part between evidences of some element ; therefore, when $A_{i1} \cap B_{i2} = \phi$, the element information is not uniform, expressed as conflict. Here, $\oplus$ represents orthogonal sum, and (1-K) is normalizing factor after eliminating conflict interference.

3. Conflict Measurement and Consistency Analysis

3.1. Evidence conflict coefficient k

According to **Definition 2**[1] (in form1) k represents the degree of contradiction between combined evidence in Dempster combination.

$$k = \sum_{A_{i1} \cap B_{j2} = \varphi} m_1(A_i) m_2(B_j) \tag{2}$$

k is the metric factor to describe the degree of inconsistency between evidences, nominated as the traditional conflict coefficient. When $k = 1$, it is completely conflict, $0 \prec k \prec 1$, it is incomplete conflict.

Construct two evidences as follows:

m_1 : $m_1(\theta_1) = 0.2$, $m_1(\theta_2) = 0.1$, $m_1(\theta_3) = 0.7$; m_2 : $m_2(\Theta) = 1$.

When $k = 0$, there exists no conflict between two evidences. Actually, compared with the completely unknown k , the evidence information k is more effective. Therefore, the traditional conflict coefficient k based on non-interaction of evidence cannot represent the inconsistency of evidences.

3.2. Information Distance

As mentioned earlier, there are a variety of distances to measure the probability function discrepancy [4-6]. This paper chooses the frequently used Jousslem information distance as a representative method of the conflict evidence distance measurement.

According to **definition 3**[4] by D-S evidence theory, under complete framework Θ, the BPA function of the two evidences is $m_1(x) = m_1(A_i), m_2(x) = m_2(B_j)$. $i = j = 1,\cdots,k$. and then the Jousselme information distance of evidence conflict is:

$$dif_J(m_1,m_2) = \sqrt{\frac{\langle m_1,m_1\rangle + \langle m_2,m_2\rangle - 2\langle m_1,m_2\rangle}{2}} \tag{3}$$

for $$\langle m_1,m_2\rangle = \sum_{i=1}^{2^{|\Theta|}} \sum_{j=1}^{2^{|\Theta|}} m_1(A_i) m(A_j) \frac{|A_i \cap B_j|}{|A_i \cup B_j|}$$

In the form, $|\cdot|$ is Modulus calculation. φ is empty set. Define $|\varphi \cap \varphi| / |\varphi \cup \varphi| = 0$, $dif_J \in [0,1]$. It is usually believed that dif_J is bigger, the greater difference between the two evidences.

Construct the two evidences as follows:

m_2 : $m_2(\theta_1) = 0.4$, $m_2(\theta_2) = 0.3$, $m_2(\theta_3) = 0.3$.

m_2 : $m_2(\theta_1) = 0.4$, $m_2(\theta_2) = 0.3$, $m_2(\theta_3) = 0.3$.

If $k = 0.66$, greater conflict exists between the two evidences. If $d_J = 0$, the elementary probability assignment function is completely the same, and at this moment, divergence occurs between the consistency of conflict feature and evidence function

The two commonly used evidence conflict measurement method mentioned above make measurement of evidence conflict respectively from the focal element of intersection and difference. Although different perspectives make the recognition of evidence conflict more comprehensive, their respective defects and inconsistencies make troubles to actual measurement. Therefore, it is advised to unite both to be utilized, but the premise of integration is the cognition of measuring both their relations with each other.

3.3. Consistency Analysis of Conflict Measurement

Because evidences of different probability functions are in different measures, conflict evidence inconsistencies differ from one another. Considering it may be associated with their own characteristics of evidences, the first thing is to make the related description for its own characteristics of evidence.

3.3.1 Uncertainty Degree of Evidence

Evidence focal element is discrete values in [0, 1], and the standard deviation and information entropy are mainly used to describe data discretization. This article chooses the information entropy to describe difference degree of inter focal element. To make the measurement more comparable, the maximum information entropy (when the focal element is mean value $1/n$, the data discretization degree is the largest, and information entropy is the largest) is used to make the normalized processing, and definition of evidence uncertainty is given based on the information entropy.

According to **Definition 4**, under complete framework Θ, if evidence M_1: $m_1(x) = m_1(A_i)$, $i = 1,\cdots,k.$, and the uncertainty degree of inter focal element of evidence M1 is:

$$V_H(m_1) = \frac{-\sum_{i=1}^{n} A_i \ln\{m(A_i)\}}{-\sum_{i=1}^{n} \frac{1}{n} \ln\{m(\frac{1}{n})\}} \tag{4}$$

$V_H(m_1)$ is nominated as evidence uncertainty degree (internal conflict degree) based on information entropy. Normalized evidence uncertainty domain is [0, 1], using relative indicators can make evidence uncertainty degree characterization more comparable.

3.3.2. Evidence Conflict Consistency Analysis Based on Uncertainty Degree

In order to gain the relationship between two common evidence measurement and evidence uncertainty, analysis are made on the evidence conflict consistency of different measurement. The paper constructs four groups of evidences with corresponding rules and substitute them into the formula (2, 3, 4) , and after calculation, the value of k , d_J and V_H can be obtained (table 1):

Table1. Correlation Analysis of Evidence Conflict Measurement k , d_J Based on Uncertainty Degree

V_H		$m(\theta_1)$	$m(\theta_2)$	$m(\theta_3)$		$m_{\oplus}(\phi)$	dif_J
0.05	m_1 m_2	0.99 0	0.01 0.01	0 0.99		0.9999	0.99
	m_1 m_2	0.99 0.99	0.01 0.01	0 0		0.02	0
0.58	m_1 m_2	0.8 0.1	0.1 0.1	0.1 0.8		0.83	0.7
	m_1 m_2	0.8 0.8	0.1 0.1	0.1 0.1		0.34	0
0.82	m_1 m_2	0.6 0.1	0.3 0.3	0.1 0.6		0.79	0.5
	m_1 m_2	0.6 0.6	0.3 0.3	0.1 0.1		0.54	0
0.99	m_1 m_2	0.4 0.3	0.3 0.3	0.3 0.4		0.67	0.1
	m_1 m_2	0.4 0.4	0.3 0.3	0.3 0.3		0.66	0

In order to make a visual analysis on the relations of uncertainty degree and the two measurements, calculation data in table 1 are shown in line diagram as follows:

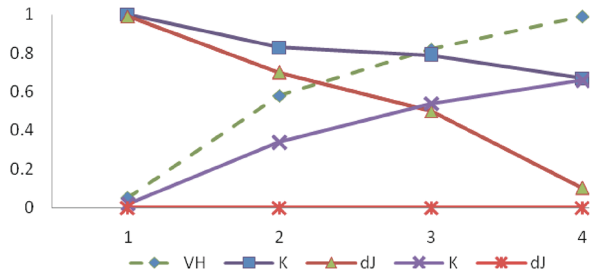

Figure 1. Evidence conflict consistency analysis based on uncertainty degree

According to figure1,distinct correlation exists between the two measurements and evidence uncertainty degree:

1. when the evidence is at uncertainty of low degree, the greater consistency is reflected on the description of the two measurement for evidence conflict. That is to say, conventional conflict coefficient k and Jousselme information distance k are at uncertainty of high degree and low degree.

2. when evidence is at uncertainty of high degree, the greater inconsistency is reflected on the description of the two measurement for evidence conflict. That is to say, conventional conflict coefficient k is less influenced by evidence and is conflict of higher degree, and information distance k belongs to lower degree.

3. As the evidence uncertainty degree gets decreasing, the two measurement k and k presents the development and change situation from consistency to inconsistency.

From analysis mentioned above, the uncertainty of evidence has influenced on different measurement results. According to the uncertainty, the measurement is divided into consistent evidence conflict and inconsistent evidence conflict.

The measurement of two evidences of low uncertainty degree is highly consistent, and the measurement of two evidences of high degree is highly inconsistent. The measurement consistency is in the middle situation for the two evidences with the different uncertainty degree or the same moderate uncertainty.

4. Comparison and Analysis of the Conflict Measurement Method

In order to analyze the specific differences and mutual relations of evidence conflict measurement influenced by different conflict measurement method, this paper constructs three evidence groups with regularity, and after substituting them into the formula

(2, 3), conflict coefficient k and Jousselme distance information are calculated (see table 1).

Table 1. Correlational Analysis of Evidence Conflict Measurement k , d_J

			$m(\theta_1)$	$m(\theta_3)$	$m(\theta_3)$	$m_{\oplus}(\phi)$	dif_J
I	1	m_1	0.99	0.01	0	0.9999	0.99
		m_2	0	0.01	0.99		
	2	m_1	0.99	0.01	0	0.02	0
		m_2	0.99	0.01	0		
II	1	m_1	0.8	0.1	0.1	0.83	0.7
		m_2	0.1	0.1	0.8		
	2	m_1	0.8	0.1	0.1	0.34	0
		m_2	0.8	0.1	0.1		
III	1	m_1	0.4	0.3	0.3	0.67	0.1
		m_2	0.3	0.3	0.4		
	2	m_1	0.4	0.3	0.3	0.66	0
		m_2	0.4	0.3	0.3		

[1] From table 1, it can be seen close mutual relation exists between the two measurements.

Through comparing three groups of evidence, it can be seen that evidence function has some influence on two kinds of measurement: within the recognition framework, when the reliability function is embodied the type of certain information, k is consistent with the characterization of d_J , and both of them are high-degree or low-degree conflict; When the reliability function is presented as uncertain information, k is inconsistent with characterization of d_J , and difference degree is positive correlated with evidence information uncertainty.

[2] By the analysis in (1), mutual relationship exists between internal contradictions and inconsistencies between evidences.

Evidence conflict is determined by the internal contradictions of evidence (uncertain) and the degree of evidence inconsistency. In evidence group I, when the contradiction between two evidences is small, evidence conflict is characterized as conflict between evidences, and the various measures are identical; in evidence group III, when the inter contradiction of two evidences is larger, conflicts characterization is relatively complex, and the various measures are not consistent..

[3] According to the evidence connotation in (2), make effective analysis on the effectiveness of several measurements:

1) In evidence group I, k is consistent with d_J in terms of characterization, and there is no absolute advantage between them. The method to measure k and d_J has the same effect compared with measuring other binary measurement.

2) in evidence group III, k is inconsistent with d_J in terms of characterization. When evidence uncertainty is low, $d_J \to 0$ and using Jousselme distance information measurement goes against the convergence after evidence fusion; Evidence conflict coefficient k is embodied as the degree of contradiction to a large degree, which cannot be directly used for characterizing conflict between evidences. The lower the uncertainty is lower, the lower the d_J characterization effectiveness of the conflict. At this moment, application literature [8] reduces the average recognition capability of high-degree conflict; however, the measurement of literature [9], [10] is almost completely dependent on the size of the conflict coefficient k .

In conclusion, the uncertainty degree of reliability function of evidence makes a great correlated influence on conflict measurement between evidences. When the evidence reliability is high, current methods are all able to be used to carry out effective conflict measurement; while the reliability of evidence is low, measurement defects will occur, and it is especially complex when measuring the evidence conflicts of different reliabilities. Therefore, this paper tries to give a conflict measurement model based on evidence uncertainty, which combines various measurement methods to ensure accurate identification of high-degree conflict.

5. Evidence Conflict Measurement Based on Uncertainty Degree

5.1 Evidence Uncertainty Degree

Basic probability assignment function of evidence is used to represent the uncertainty of information, and the basic function of information fusion is to eliminate the uncertainty of information. Therefore, from the perspective of information value, the more concentrated the probability assignment of evidence focal element, namely, the greater the difference among the focal element, the higher the effect (value) of evidence information, and the smaller the internal conflict of evidence. On the contrary, the more average the focal element, the higher the evidence uncertainty, and the inter contradictions exist among evidences. Therefore, the reliability function with the same focal element assignment is equivalent with completely uncertain evidence. Useful information is not offered in the absence of supplement of other evidence. It is important to note that the completely uncertain here is different from completely unknown of $m(\varphi)$. The uncertainty value information and the size of the uncertainty degree is on behalf of the size of the information value, and $1/n$ non-value information.

Evidence focal element is discrete values between

[0, 1] and is used to describe data discretization mainly including the standard deviation and information entropy. This article chooses the information entropy to describe focal element difference degree of evidence. To make the measurement more comparable, the maximum information entropy (when the focal element is mean value $1/n$, the data discretization degree is the largest, and information entropy is the largest) is used to make the normalized processing, and definition of evidence uncertainty is given based on the information entropy.

According to **definition 7**, under the complete framework Θ, evidence M_1: $m_1(x) = m_1(A_i),\ i = 1,\cdots,k$. and then the uncertainty degree of inter focal element of evidence M1 is:

$$V_H(m_1) = \frac{-\sum_{i=1}^{n} A_i \ln\{m(A_i)\}}{-\sum_{i=1}^{n} \frac{1}{n} \ln\{m(\frac{1}{n})\}} \tag{5}$$

$V_H(m_1)$ is nominated as evidence uncertainty (inter conflict degree) based on information entropy. The range of normalized evidence uncertainty is [0, 1], and using relative indicators make evidence uncertainty degree representation more comparable.

In decision-making system, evidence extraction is the foundation of the further integration of information. Evidence with larger uncertainty on the one hand, is not conducive to the formation of decision-making information; on the other hand, the generation of high-degree uncertainty evidence is often caused by recognition framework set faults or information source donor breakdown. Therefore, measurement and identification of evidence with higher uncertainty be improved in conflict identification.

Specific values of uncertainty is influenced by the amount of the evidence focal element (if the number of evidence focal element is less, the evidence uncertainty value is higher). A single data fails to account for the high-low state of uncertainty. For example, when $V_H = 0.73$ for $m(0.1, 0.2, 0.7)$, the uncertain value is bigger. But it is clear that evidence has great information value. When making comparison of the evidence with the same focal elements, the bigger the information entropy, the greater the conflict within evidences, and the higher the evidence information uncertainty, and vice versa. Therefore, flaws exist in the measurement threshold selection for the uncertainty as a separate conflict identification factor. However, the uncertainty as an important supplementary condition can increase the identification capability of evidence conflict especially high-degree conflict.

5.2 The Conflict Measurement Method Based on Evidence Uncertainty Degree

Known by the analysis above, evidence uncertainty degree has the relevant influence on the evidence conflict measurement methods. Besides, in order to compensate for the defects of various measurement methods, this paper introduces evidence degree as synthetic factor on the basis of the existing conflict coefficient k and Jousselme distance information binary measurement. And it offers a new evidence conflict measurement method which can reflect characteristics of evidence itself and adapt to the complex situation.

Definition 8

$$conflict(m_i, m_j) = w_1 k + w_2 d_J \tag{6}$$

In this form, $w_{1,2}$ is conflict synthetic factor based on the evidence uncertainty. Assume two evidence groups m_i, m_j, and uncertainty $V_{Hi} \geq V_{Hj}$, for $w_1' = V_{Hj}$, $w_2' = 1 - V_{Hj}$. because V_{Hi}, V_{Hj} is uncorrelated, then $w_1' + w_2' \neq 1$. By normalizing the synthetic factor, it can be obtained:

$$w_1 = \frac{V_{Hi}}{V_{Hi} + 1 - V_{Hj}} \quad w_2 = \frac{1 - V_{Hj}}{V_{Hi} + 1 - V_{Hj}},$$

$w_1 + w_2 = 1$, and $w_1 \geq w_2$, uncertainty empowerment “expands” the function of conflict coefficient k during measurement inconsistency, to reflect the relative influence of two kinds of measurement. it makes the conflict measurement more in line with the analysis of the connotation of evidence conflict.

6. Check Analysis

To test the effectiveness of the conflict identification method based on the uncertainty degree, 6 pieces of evidence information are set in simulation set information. And the basic probability distribution function is $m_i\ (i = 1, 2\cdots, 6)$, and the system identification framework is $\Theta = \{A, B, C\}$. Specific evidence information is shown in table 2, among them, there exists significant difference between m_4, m_6 and the other evidences, and evidence m_3 is of highest uncertainty degree.

Table 3. Information data of simulated evidence

	$m(A)$	$m(C)$	$m(C)$	VH
m1	0.8	0.1	0.1	0.58
m2	0.8	0.05	0.15	0.56
m3	0.4	0.3	0.3	0.99
m4	0.1	0.2	0.7	0.73
m5	0.75	0.15	0.1	0.67
m6	0.2	0.2	0.6	0.86

In order to increase the general analysis and simplify the problem, after taking the six pieces of evidence information into pair combinations, and 21 groups of evidence combination can be gained. Substitute it into the formula 2-8, and calculate evidence conflict coefficient of (m_i, m_j) d_J, Jousselme distance information d_J, literature [8], literature [10] and conflict proposed in this paper based on the uncertainty degree. The evidence conflict comparison data under several measurement methods are shown in Table 3.

Table 3. Comparison of evidence feature under several measurement methods

Measurement	k	d_J	Jiang[8]	Liu[10]	*conf*
m_{11}	0.34	0.00	0.17	0.00	0.20
m_{12}	0.34	0.05	0.20	0.13	0.21
m_{13}	0.62	0.35	0.48	0.46	0.54
m_{14}	0.83	0.66	0.74	0.75	0.77
m_{15}	0.38	0.05	0.21	0.14	0.25
m_{16}	0.76	0.56	0.66	0.67	0.69
m_{22}	0.34	0.00	0.17	0.00	0.19
m_{23}	0.62	0.35	0.49	0.47	0.54
m_{24}	0.81	0.64	0.72	0.73	0.74
m_{25}	0.38	0.09	0.23	0.18	0.26
m_{26}	0.74	0.54	0.64	0.65	0.67
m_{33}	0.66	0.00	0.33	0.00	0.65
m_{34}	0.69	0.36	0.53	0.50	0.62
m_{35}	0.63	0.30	0.46	0.44	0.54
m_{36}	0.68	0.26	0.47	0.42	0.63
m_{44}	0.46	0.00	0.23	0.00	0.34
m_{45}	0.83	0.63	0.73	0.73	0.76
m_{46}	0.52	0.10	0.31	0.23	0.42
m_{55}	0.41	0.00	0.20	0.00	0.27
m_{56}	0.76	0.53	0.64	0.65	0.69
m_{66}	0.56	0.00	0.64	0.00	0.48

In order to present the features of evidence conflict measurement methods proposed in this paper in a more intuitive and clear way, combine the value of the 20 evidence groups in table 3, respectively with conventional conflict coefficient k of unitary measurement, the distance information d_J and binary measurement proposed by Jiang[8], Liu[10] into a line chart to make comparisons , as shown in figure 1 and figure 2.

Seen from figure 2, conflict measurement *conf* based on the evidence uncertainty degree proposed in this paper has the identical trend with the traditional conflict coefficient d_J and the information distance d_J , which proves the effective of this method in conflict measurement. Compared with two kinds of unitary measurement, the method proposed in this paper has the features: (1) it effectively solves the conflict inconsistency when recognizing the two same evidence conflicts, $d_{ij} = 0\,(i = j)$ but $k_{ij} \neq 0$. It is of universality; (2) it shows the uncertainty degree influence on evidence conflict measurement. Since the high-degree uncertainty of the evidence 3 has great differences of measurement conflict between m_3 and other evidences, this paper presents methods that by weighting to extend the traditional role of conflict k . It is more suitable for the connotation that the contradiction is concurrent by internal and external contradictions.

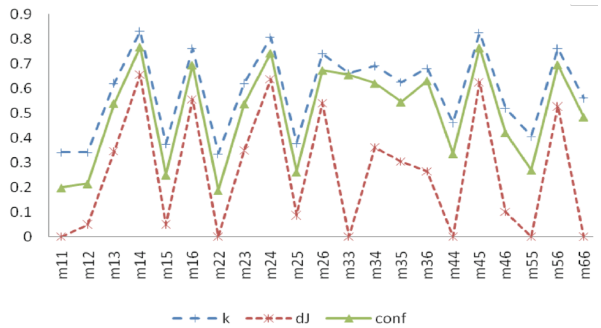

Figure 2. The comparison of evidence conflict measurement *conf* , k and d_J

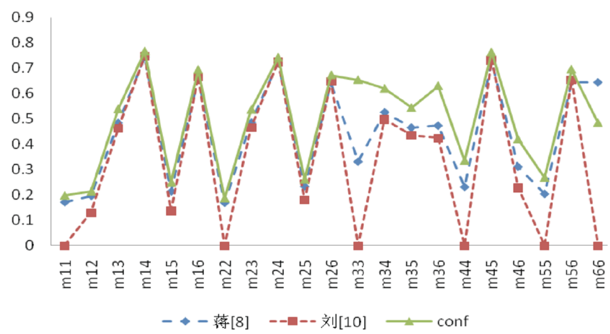

Figure 3. Comparison of Three kinds of Binary Metric

From figure 3, it can be seen it is a strong match of the proposed measurement method with the two kinds of binary measurement mentioned above, which proves its effectiveness again. The advantages of the method is that: [1] conflict measurement method based on evidence uncertainty cannot only guarantee the effective measurement for high-degree conflict evidence, but also have the “highly” expanding effect, thus more favorable to improve the recognition accuracy of high-degree conflict;[2] the method expands the evidence conflict value with larger uncertainty through weighting. It implements the requirement put forward as section 4.1 to improve conflict measurement with higher uncertainty and identification capability, and it separate the evidence information with higher uncertainty effectively in the system;[3] combined with the specific categories of information, a preliminary analysis on the conflict-produced essence and highly conflict treatment scheme is offered: assume when six evidences are information of homogeneity and homology, according to the evidence conflict metrics evidence 3, 4, 6 can be directly recognized as high-degree conflict evidence and get rid of them. Evidence fusion is carried out after checking and verifying the information donor; when they are information of heterogeneity and homology, it is not unreasonable that evidence 3, 4, 6 exist high-degree conflict. First of all, analysis of isolation should be carried out, after excluding donor failure, choose corresponding integration mode; if they are homogenous and heterologous information, it is reasonable to make direct analysis of high-degree conflict evidence without influencing evidence fusion.

7. Conclusion

One of the main constraints of the application of D-S evidence theory is the measurement and identification of high-degree evidence conflict. Due to different sources of information, it causes substantial complexity on conflict and the inconsistency of measurement under different measurement method add the difficulty for identification, and improper handling may lose important information leading to the decision-making mistakes. In this paper, based on high-degree evidence conflict identification method of uncertainty, in view of the internal contradiction's influence on the conflict measurement, revision is made on evidence conflict measurement on the basis of binary measurement. Through simulation, high-degree conflict feature recognition method based on the uncertainty solves the problem of the previous measurement conflict inconsistency. And it reflects the connotation of the conflict and the reasonable analysis for the conflict essence. In particular, it strengthens identification ability of the conflict of evidence and provides evidence security and effective treatment for information fusion.

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