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The Algorithm Aiming at Conflict to Improve DS Evidence Theory

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Abstract: For issues like one ticket veto, improper distribution and high reliability conflict which in Dempster-Shafer (DS) evidence theory, this study has put forward an improved method to overcome these problems. This method is still cited DS evidence theory synthesis formula and redistribute the main evidence source. This study has considered importance of fusion system's evidence and use the evidence right to express the conflict distance. It also considered different evidences to the same focal with different support. Evidence consistency and the concept of focal importance to recombine the source information have been used. Finally, through the synthesis formula of the DS evidence theory to fusion the evidences, compared with other scholar's algorithm and it has been found that the results of the new algorithm is perfect and could solve the problem of one ticket veto and other DS theory's defects.

Key words: DS evidence theory, information fusion, conflict distance, focal

INTRODUCTION

Information fusion is an information processing technology proposed in 1980s, it is used for solving the information processing problem of multi-sensor system. It also can be used for target recognition, military command, situation assessment, comprehensive control, medical diagnosis, fault diagnosis, market strategy and investment decision-making, etc. (Cheng *et al*., 2006; Fan and Li, 2006; Peng *et al* 2009; Cheng, 2008; Li and Wang, 2011). More and more people consider the problems of information fusion with different sorts. Now, decision-level information fusion is the key technology of the fusion technology. Compared with Bayesian probability reasoning method, DS evidence theory can deal with the issues of information inaccurate and information unknown. It can also satisfy the axioms weaker than probability. But there also exists the problem of counter-intuitive conclusion in DS evidence theory. Domestic and foreign scholars did lots of research to solve the problems of DS evidence theory which are basically divided into two ideas. One idea is represented by Takahiko (1998), Matsnvama (1994), Toshiyuki (1991), Lefevre *et al.* (2000, 2002), Zhang *et al.* (2001), Xiang and Yongxiang (2000), Dubois and Prade (1988), Sun *et al.* (2000) and Wen *et al.* (2010). They believed the most important problem in evidence combination is how to redistribution the conflict. The other idea is represented by Murphy (2000), Josang *et al.* (2003), Yong *et al.* (2004), Shafer (1992), Hai-Yanl *et al.* (2008), Tian-Lu and Pei-Wen (2005) and Zhang and Huan-zhang (2006). They think pretreatment of the conflict evidence can effectively solve the fusion problem.

DS EVIDENCE THEORY

Evidence theory (You and Guo-hong, 2000; Zadeh, 1979), also called Dempster Shafer evidence theory, Dempster used the probability range to simulate the uncertainty, Shafer improved the Dempster's work and expanded the evidence reasoning to handle those not sure, not precise memory interval or inaccurate information. At present the main application fields of Dempster Shafer theory are decision-making and prediction.

The basic theory of DS is defined as follows:

- **Define 1:** Set Θ is the distinguish framework, m: $2^{\Theta}\rightarrow$ [0, 1] is the BPA (Basic Probability Assignment), the elements of which are mass function in Θ. These functions need to meet the following conditions:

$$\begin{cases} m(\varnothing)=0 \\ \sum_{A\subseteq\Theta} m(A)=1 \\ m(A)>0 \end{cases} \quad (1)$$

Among them, A is focus element in mass function, $\bigcup_{m(A)>0} A$ is the core of mass.

- **Define 2:** The synthesis law of two reliabilities:

$$m(A)=m_1\oplus m_2(A)=\frac{\sum_{A_i\cap B_j=A} m_1(A_i)m_2(B_j)}{1-\sum_{A_i\cap B_j=\varnothing} m_1(A_i)m_2(B_j)} \quad (2)$$

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Noticeable:

$$K = \sum_{A_i \cap B_j = \varnothing} m_1(A_i)\, m_2(B_j)$$

is the two evidence's conflict function.

DS EVIDENCE THEORY'S SHORTCOMINGS

The rationality of combinatorial theory is proved in theory by Dempster and Shafer. Other algorithms in dealing with uncertainty can not be compared with DS evidence theory. Actually the utilization of DS evidence theory may cause some problems. We often use examples to analyze the insufficient of DS evidence theory.

Ex 1: Two groups of Basic Probability Assignment (BPA) evidence reports are shown in Table 1.

After evidence combination formula, we can obtain the fusion results as:

$$m(A) = 0\ m(B) = 0\ m(C) = 1$$

$$K = 0.9999$$

Results show that fusion target is C. This is obviously against with our normal cognition. In DS evidence theory, K reflects the conflict between evidences. In this example it is concluded that K is 0.9999, it means that the conflict between two groups of evidence is considerable. The fusion result is not advisable in this situation.

It shows that evidence theory in dealing with excessive conflict issues has limitations.

Ex 2: Two groups of BPA evidence report is shown in Table 2.

After evidence combination formula, we can obtain the fusion results as:

$$m(A) = \frac{1}{3}\ m(B) = \frac{1}{3}\ m(C) = \frac{1}{3}$$

$$K = 0.25$$

In this example, the conflict factor is 0.25, it shows that the conflict between evidences is not that big, This phenomenon can be attributed to the improper distribution of reliability. So before making final decision based on DS combination rules, we need a reasonable distribution of evidence.

Table 1: Evidence's BPA for Ex1

Evidence	A	B	C
m_1	0.99	0	0.01
m_2	0	0.99	0.01

Table 2: Evidence's BPA for Ex2

Evidence	A	A∪B	B∪C	C
m_1	0.5	0	0.5	0
m_2	0	0.5	0	0.5

Table 3: Evidence's BPA for Ex3

	A	B	C
m_1	0.50	0.2	0.30
m_2	0.00	0.9	0.10
m_3	0.55	0.1	0.35
m_4	0.55	0.1	0.35

Ex 3: We give some evidences groups and make the fusion according to the DS evidence theory evidence (Table 3).

After evidence combination formula, we can obtain the fusion results as:

$$m(A) = 0\ m(B) = 0.3288\ m(C) = 0.6712$$

$$K = 0.9945$$

The fusion results clearly not fit to people's normal logic, the reason of this kind problem is that the basic trust distribution of {A} is 0 which from the second evidence. The result of {A} always equals to zero, no matter how much the basic trust distribution from other evidences support {A}. Owning the characteristics of one ticket veto, this shortcoming for DS evidence theory is very deadly.

THE IMPROVED ALGORITHM OF DS EVIDENCE THEORY

When we measure the conflict evidence, it is not enough to consider the comprehensiveness among evidences lonely. Because it can't comprehensively reflect the actual conflict, we need to consider the other among evidences. Namely, the degree of the basic probability distribution of focal also has influence on conflict among evidences. The pre-treatment process of evidence is the key to get the perfect fusion result. The conflict factor of DS evidence theory is not the right response to conflict level between the evidences. Rationally introducing a new conflict formula to correct response the conflict level is the entry point to evidence conflict problems.

Evidence consistency: Since the conflict factor of DS evidence theory cannot effectively reflect the real conflict situation of two groups of evidences, we introduce

distance functions (Jousselme *et al*., 2001) to solve this problem.

Define 3: m_1 and m_2 are the evidence's BPA in recognition framework. The distance between m_1 and m_2 can be expressed as:

$$d(m_1,m_2)=\sqrt{0.5\times(\langle m_1,m_1\rangle+\langle m_2,m_2\rangle-2\times\langle m_1,m_2\rangle)} \quad (3)$$

$$\langle m_1,m_2\rangle=\sum_{i=1}^{2^N}\sum_{j=1}^{2^N} m_1(A_i)\,m_2(A_j)\frac{|A_i\cap A_j|}{|A_i\cup A_j|} \quad (4)$$

d (m_1, m_2) is the difference between two evidences. The more the difference is, the more the conflict is.

The support degree between two evidences can be expressed as:

$$suport(m_i)=\sum_{i=1,j=1}^{m} 1-d(m_i,m_j) \quad (5)$$

By normalizing the support degree of the evidence, we can get the consistency parameters:

$$\gamma_i=\frac{suport(m_i)}{\max(suport(m_i))} \quad (6)$$

$$M=\sum_{i=1}^{m} m_i*\gamma_i \quad (7)$$

γ_i reflects the credibility proportion of evidences. It can also reduce the influence of fusion result by low credibility evidence.

Importance of focal: Evidence theory is concerns the fusion about focal element. The reasonable processing about focal element may play an important role to the fusion result.

Define 4: We can redefine the BPA in recognition framework as:

$$Set\,P_m(A)=\sum_{B\in\Theta}\frac{|A\cap B|}{|B|}m(A) \quad (8)$$

$|A|$ express the number of elements contained in A. Set P_m (A) is the support degree of each subset from basic probability distribution. The degree of uncertainty will be assigned as the follow formula:

$$Set\,P_m(\Theta)=1-\sum\sum_{B\in\Theta}\frac{|A\cap B|}{|B|}m(A) \quad (9)$$

The conflict can be computed by the same focal under different evidences:

$$Diff_{m_i}^{m_j}(x_t)=\left|Set\,P_{m_i}(x_t)-Set\,P_{m_j}(x_t)\right| \quad (10)$$

We use the conflict size to decision the reliability of focal and redistribution the evidence's quality function:

$$\alpha_{x_t}=\exp(-Diff_{m_i}^{m_j}(x_t)) \quad t=1,2,...,n \quad (11)$$

$$m_i^*=\alpha_{x_t}\times m_i \quad i=1,2...N,\ t=1,2,...,n \quad (12)$$

$$m^*=\frac{m_i^*}{\frac{1}{N}\times\sum_{i=1}^{N} m_i^*} \quad (13)$$

Among the above formulas: i is the group of evidences and t is the focal of evidence.

The new algorithm is based on the evidence consistency and the importance of focal. It uses the distance function to measure the conflict between reasonable evidences. And the new algorithm combined the evidence consistency and the important of focal to improve the data decision.

The specific steps of new algorithm as follows:

- Calculate the evidence consistency from Eq. 3-7
- Calculate the important of focal from Eq. 8-13
- Get the weight from ① and redistribution them to evidence, acquire the new evidence distribution function M
- Get the weight from ① and redistribution them to evidence, acquire the new evidence distribution function m*
- Use the DS evidence synthetic formula to synthesis the distribution function which get from ③ and ④

This article will through a series of simulation experiments show the rationality and effectiveness of the new algorithm.

THE SIMULATION EXPERIMENT

Firstly, we applied the new algorithm to simulation for Ex 1, 2 and 3.We get the fusion results which are shown in Table 4.

Table 4: Fusion result of different situation

	A	B	C
Ex 1	0.4997	0.4997	0.0005
Ex 2	0.3750	0.2500	0.3750
Ex 3	0.1513	0.7105	0.1381

Table 5: Fusion result of different algorithms

	Evidence											
	m_1, m_2				m_1, m_2, m_3				m_1, m_2, m_3, m_4			
Algorithm	A	B	C	Θ	A	B	C	Θ	A	B	C	Θ
Yager	0	0.18	0.03	0.79	0	0.0180	0.0105	0.9715	0	0.0018	0.0037	0.9945
Murphy	0.1543	0.7469	0.0988	0	0.3371	0.5751	0.0878	0	0.8066	0.1532	0.0403	0
Zhang	0.1543	0.7469	0.0988	0	0.6602	0.2072	0.1326	0	0.9650	0.0034	0.0316	0
Liu	0.2500	0.5500	0.2000	0	0.4136	0.3096	0.2769	0	0.4659	0.2303	0.3038	0
Jiang	0	0.1107	0.0031	0.8863	0	0.0008	0.0003	0.9989	0	0	0	1
Chen	0.2500	0.5500	0.2000	0	0.4961	0.1907	0.3132	0	0.4564	0.0897	0.2270	0.2270
This study	0.1513	0.7105	0.1381	0	0.4168	0.3381	0.2451	0	0.5269	0.1998	0.2733	0

By the fusion results we can conclude that the evidence fusion result of Ex 1 which calculated from the algorithm of this study is content people's normal cognition. It solved the problem of evidence conflict excessive. The fusion result of Ex 2 shows that this algorithm is adequate in solving the problem of reliability improper distribution and has obvious superiority. The fusion result of Ex 3 reflected the algorithm could solve the phenomenon of one ticket veto and getting the fusion result accord with our logic. Card above all, it means that the algorithm has robustness.

Secondly, this study will compare with some classic DS evidence theory algorithms. We will demonstrate the superiority of the new algorithm. We applied the evidence from Ex 3 to make the fusion. The results are shown in Table 5.

After simulation the evidence which provided by Ex 3, we can clear observe the result in Table 5. The algorithm by Yager and JIANG are prone to the phenomenon of one ticket veto. The algorithm of Murphy excessive exaggerated the single evidence. The algorithm of Zhang is excessive exaggerated the useful information and weaken the other elements, it easy to lose the useful information of not main focal. The algorithm of LIU is relatively tending to conservative and it cannot explicitly point out the target elements. The algorithm of CHEN easily weakening useful information and strengthen the unknown information. This paper's algorithm can be easily used to solve the issues of highly conflict and one ticket. When the algorithm dealing with the extreme problems, it always performance stability. It uses the formulas to estimate the focal proportion and reasonable judgment out the target.

CONCLUSIONS

DS evidence theory has some problems such as highly conflict, one ticket veto, reliability improper distribution etc. This study puts forward improved ideas and methods to overcome the phenomenon. Through the simulation experiment we know that the algorithm can solve the above problems reasonably and accurately. We can get the relatively accurate judgment by the algorithm we proposed in this study. And compared with other scholar's algorithm this paper's algorithm exist certain advantage at compatibility, accuracy and robustness etc. In future study and research, we hope to use this algorithm into the decision making of multi-sensor information fusion.

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