A New Method of Information Decision-making Based on D-S Evidence Theory

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Abstract— **D-S evidence theory is a method broadly applied in fusion for decision-making. However, this theory has some shortcomings in the formula of evidence combination with the exception that evidence of fully conflict can not be combined, then the probability validity is difficult to determine and sometimes the composed evidence is different from people's subjective judgments or some other issues. These confine the application of evidence to some extent. Some of them have the dubious credibility which affects the fusion result when Multi evidence are combined together. In order to expand the application of the formula of this theory and enhance the reliability of the fusion results, a new combination formula is introduced in this paper, which is also compared with other formulas in other literatures and finally the improved reliability of this combination formula is verified. At last, through data-mining of the decision-making information on a number of isolated points, a new method using combined evidence to make decisions is described. It's proven from the experimental results that the new combination method not only works well and effectively in the evidence of a high level of conflict but also is applicable to fusion for decision-making .**

Index Terms—**D-S evidence theory, combination rule, reliability, evidence isolated point**

I .INTRODUCTION

D-S evidence theory was first proposed by Demusite[1]. Shafer expanded the theory[2], developed and organized it into a comprehensive theory of mathematical reasoning[3]. It can be considered an expansion of the classical theory of probability reasoning in a limited domain[4]. Its main feature is the support for describing different levels of accuracy[5]. The Dempster's rule of combination is a widely used technique to integrate evidence collected from different sources as P. Bhattacharya described in [6].

In the evidence theory, a belief function is introduced to measure uncertainty[7]. The similarity function to deal with uncertainty is cited without prior knowledge, compared with the subjective Bayesian method[8]. D-S evidence theory provides a useful approach that can integrate the evidence provided by multiple sources[9], but there are some inadequacies in the fusion formula, the synthesis results may be problematic[10]. The construction of the basic probability assignment function in the D-S evidence theory and its preliminary exploration are given in [11].

According to the actual situation, how to construct the basic probability assignment function in the D-S evidence theory, its preliminary exploration was done in [16] and a basic probability assignment function of a specific formula was constructed in accordance with the decision-making, which worked well. Research work in this paper includes the following two primary aspects. Firstly, a new formula for combination is put forward. Secondly, by the combination of data mining and evidence processing, the introduction of evidence credibility and the pre-processing of evidence are depicted. Thirdly, the combined evidence in this paper using evidence combination formula is presented and its result of is compared with other formulas.

II .RELATED WORK

Chen[12] presented that rough set theory can complement probability theory, evidence theory, fuzzy set theory, and other approaches, because the ability of rough set theory can handle the inherent uncertainty or vagueness of data. Recent advances in rough set theory have made it a powerful tool for data mining, pattern recognition, and information representation. Many information fusion applications are

978-1-4244-6588-0/10/$25.00 ©2010 IEEE

often characterized by a high level of complexity because: 1) data are often acquired from sensors of different modalities and with different degrees of uncertainty; 2) decisions must be made efficiently; and 3) the world situation spans a time period. To address these issues, Zhang[13] proposed an information fusion framework based on dynamic Bayesian networks to provide active, dynamic, purposive and sufficing information fusion in order to arrive at a reliable conclusion with reasonable time and limited resources. The proposed framework was suited to applications where the decision must be made efficiently from dynamically available information of diverse and disparate sources. Elouedi[14] put forward a method for assessing the reliability of a sensor in a classification problem based on the transferable belief model. The discounting factors are computed on the basis of minimizing the distance between the Pignistic probabilities computed from the combined discounted belief functions and the actual values of data. Huynh[15] reanalyzed the evidential reasoning (ER) approach explicitly in terms of D–S theory and then proposed a general scheme of attribute aggregation in MADM under uncertainty. Theoretically, it was shown that new aggregation schemes also satisfy the synthesis axioms under linguistic assessments. But further research should be done.

Ⅲ.DEFINITION

D-S evidence theory is a theory based on a non-empty collection, which is also called the sample space. The space consists of a number of limited and mutually exclusive elements. Definition is expressed by the collection. Any definitions to the problem domain should be defined in the power set, to which we defined a probability assignment function *m*: whose range is *[0,1]*, *m* satisfies $m(\Phi)=0$, and all the values of the basic probability functions are summed to 1. *m (A)* expresses the level of trust to assumption sets *A* based on the current environment. On the basis of probability assignment function, we define two functions on the power set: credit function *Bel* and the likelihood function *Pl*. Credit function *Bel (A)* expresses the degree of support for Proposition *A*, that is the true extent of *A*; the likelihood function *Pl (A)* represents the false extent of *A*, *[Bel (A), Pl (A)]* constitutes the range of evidence, which shows the degree of uncertainty of evidence.

The evidence theory provides a useful evidence combination function; the combination formula is as follows:

$$m(\Phi)=0$$

$$m(A)=\frac{1}{1-k}\cdot\sum_{A_i\cap B_j\cap C_l\cap\ldots=A} m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)\ldots,\ \forall A\in\Theta$$

where $k=\sum_{A_i\cap B_j\cap C_l\cap\ldots=\phi} m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)\ldots$

The value of k reflects the conflict degree between the evidence. The coefficient *1 / (1-k)* is a normalization factor, whose role is to avoid assigning non-zero probability to empty set in combination.

From the previous statement, it is clear that we can not use the above formulas to synthesize the evidence when $k=1$. It is of a high degree of conflict between evidence when k is close to *1*; the above formula will produce perverse results. Detailed examples are shown in [16].

For the credit of evidence source, we introduce the function *cre(S)* in [17] . They are based on simulation of the degree of consistency between evidence to reflect the support degree among them. For consistency, we must introduce the concept of evidence distance. Assume a number of *N* propositions that are different from each other within an identification framework, there are evidence sources of *N*: s_1 , s_2 , s_3 ,...with corresponding basic probability assignment function: m_1, m_2, m_3,....Each source of evidence s_i can be seen as a 2^n dimension row vector. The various components of vector respectively correspond to various elements m_i of the probability distribution values of the power set 2^{Θ}. The distance[18] between the two sources s_i, s_j and they can be defined as:

$$d(s_i,s_j)=\sqrt{\frac{1}{2}(s_i-s_j)D\left(s_i-s_j\right)^T} \qquad (1)$$

Where, D is an $2^N\times 2^N$ matrix, whose elements are $D(A,B)=|\frac{A\cap B}{A\cup B}|, A,B\in 2^N$.The distance between evidence s is :

$$d(s_i,s_j)=\sqrt{\frac{1}{2}(\|s_i\|\cdot\|s_i\|+\|s_j\|\cdot\|s_j\|-2<s_i,s_j>)} \quad (2)$$

in the formula,

$$<s_i,s_j>=\sum_{s=1}^{2^N}\sum_{t=1}^{2^N} m_i(A_s)m_j(A_t)\left|\frac{A_s\cap A_t}{A_s\cup A_t}\right| \quad (3)$$

Where, $A_s, A_t\in 2^{\Theta}$, $|N_k(s_i)|$ is the number of all the evidence of k-distance. A number of K objects are selected with the highest LOC value, which is called the isolated points of evidence.

Here we propose 5 definitions.

Definition 1: The sum of the local distance of evidence s_i $LDS_k(s_i)$ is defined as the summed distance of the evidence s_i and its closest neighboring evidence of a number of K. Formula is as follows: $LDS_k(s_i)=\sum d(s_i,s_j)$, where $d(s_i,s_j)$ is the evidence distance between the evidence s_i and the evidence s_j.

Definition 2: k-Distance.

From the actual distances of all K closest neighboring evidence to evidence s_i, choose the greatest evidence distance as the k-distance.

Definition 3: Local isolation factor $LOC(s_i)$ of evidence s_i is defined as a ratio of the sum of local evidence distances to the evidence s_i with mean value of the evidence of the local distances in k-distance. Formula is as follows:

$$LOC(s_i)=\frac{lds_k(s_i)}{\frac{\sum_{o\in N_k(s_i)} lds_k(o)}{|N_k(s_i)|}} \quad (4)$$

where, $N_k(s_i)$ expresses k-distance of evidence s_i.

Great LOC value means that the evidence surrounding the evidence s_i offer support, while the low-LOC value states that the evidence to support the evidence has a relatively high distribution density.

$LOC(s_i)$ can be used to simulate the isolation level of the evidence s_i; and its value is always greater than 0. We use $\frac{1}{loc(s_i)}$ of the evidence s_i to simulate its support level from other evidence so that we can define a credibility degree formula of evidence s_i:

$$cre(s_i)=\frac{\frac{1}{loc(s_i)}}{\sum_{i=1}^{N}\frac{1}{loc(s_i)}} \quad (5)$$

From the equation, we can see that the sum value of all the evidence credibility is 1. Clearly, the higher level of evidence in isolation is, the smaller the probability and the credibility of other evidence with support will be.

Definition 4. The overall credibility of the evidence source ***cf*** was first introduced in [8]. In [8], 22 uniformity between evidence was used to construct the overall and the fully consistent credibility super-sphere of the evidence, which is all $m\bullet(m-1)$ dimensions with respective radius r and R, defined as:

$$r=\sqrt[C_M^2]{\sum_{i=1}^{M-1}\sum_{j=i-1}^{M} coh^{C_M^2}(s_i,s_j)}\Big/2$$
$$R=\sqrt[C_M^2]{C_M^2\times 1^{C_M^2}}\Big/2=\sqrt[C_M^2]{C_M^2}\Big/2 \quad (6)$$

Considering the credibility of the evidence source is one-dimensional, we define the overall credibility of the source of evidence $cf=r/R$.

Definition 5. Isolated points of evidence: the evidence that has totally inconsistent characteristics or behaviours than the majority evidence in the source. By analyzing these isolated points with data-mining algorithm, we learn that the evidence with low credit provides no useful information and does not affect the distribution of focal elements; therefore the effectiveness of evidence integration can be improved and enhanced.

IV. EVIDENCE FUSION BASED ON DATA MINING AND D-S EVIDENCE THEORY

This section will employ data mining and D-S evidence theory for decision-making. In a being fused system framework, firstly, the initial decision-making information from each local arbiter is obtained through the method in [11], then the focal element's basic probability assignment function is worked out in each information group under the fusion system framework. After obtaining these distribution functions, we get all the decision-making information from local arbiter as an evidence. The basic probability assignment function of various focal elements under the integrated framework is equal to the basic probability assignment function for each evidence's focal element in the evidence theory. From the practical engineering point of view, various improvements to the *Dempster* combination rule do not reduce the computation workload of the system, the evidence to be integrated may amount to hundreds or thousands in the actual application system, so to reduce system computing workload in the future work, we commonly will use local calculations method, as these improvements do not appear to meet the combination rules, so the calculation can not be localized[19].

In this paper, the idea is that, to the hundreds of thousands of evidence, a pre-treatment to the evidence integration is done at first, mainly through the data mining to the isolated points and then the fusion is performed. The basic principle of data mining algorithm is, firstly, to circulate the distance between any evidence $\boldsymbol{p}$ and other evidence in the evidence set, then to select the smallest distances(a number of K), the maximum of which was k-distance of evidence $\boldsymbol{p}$, while the sum value of which were the summed local distance *(LD-Sk(p))* of evidence $\boldsymbol{p}$. The next step is to find out all neighboring evidence whose distance to evidence $\boldsymbol{p}$ are not greater than the k-distance, and to work out the local isolation coefficients of evidence $\boldsymbol{p}$. The final and crucial step is to select the n-value of the objects with the greatest LOC as isolated points from the data sets. One point needs to be explained, that is $\boldsymbol{n}$ equals to the threshold value multiplied by the total number of the product.

Through the analysis of the previous steps, we know that, there are some certain defects of the combination formula in D-S evidence theory, then, based on this point, we propose a new combination rule 1 as follows:

$$m(\Phi)=0$$

$$p=\sum_{A_i\cap B_j\cap C_l\cap\ldots\neq\Phi} pt\cdot m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)\ldots$$

$$pt=\frac{|A_i\cap B_j\cap C_l\cap ..|}{|A_i|+|B_j|+|C_l|+\ldots-|A_i\cap B_j\cap C_l\cap ..|}$$

$$m(A)=\frac{1-k}{p}\cdot\sum_{A_i\cap B_j\cap C_l\cap\ldots=A} pt\cdot m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)..$$

$$+k\cdot cf\cdot\sum_{i=1}^{M}(m_i(A)\cdot cre(S_i))$$

$$k=\sum_{A_i\cap B_j\cap C_l\cap\ldots=\Phi} m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)\ldots$$

$$m(\Theta)=\frac{1-k}{p}\cdot\sum_{A_i\cap B_j\cap C_l\cap ..=\Theta}\frac{|\Theta|\cdot(m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)\ldots)}{|A_i|+|B_j|+|C_l|+\ldots-|\Theta|}$$

$$+k\cdot(1-cf)+k\cdot cf\cdot\sum_{i=1}^{M}(m_i(\Theta)\cdot cre(s_i))$$

Where, $\boldsymbol{k}$ represents the total conflicts of all evidence. $\boldsymbol{p}$ is used to simulate the overall probability of the consistent evidence after cross-fusion. From the above statement, it is obvious that the more consistency between the evidence source is, the greater value of $\boldsymbol{p}$ is. $\frac{|A_i\cap B_j\cap C_l\cap ..|}{|A_i|+|B_j|+|C_l|+\ldots-|A_i\cap B_j\cap C_l\cap ..|}$ reflects the extent of cross-integration among evidence. To the group credit of the evidence source: *cf*, generally, it can be considered as the close extent to the ideal source with full consistence.

The proof of the combination Formula 1 is showed as follow.

According to formula1: $\sum_{A\subset\Theta} m(A)=1$。

$$\text{Prove: }\sum_{A\subset\Theta} m(A)=m(\Phi)+\sum_{\substack{A\subset\Theta\\ A\neq\Phi\\ A\neq\Theta}} m(A)+m(\Theta)=1$$

$$=\frac{1-k}{P}\Big[\sum_{\substack{A\subset\Theta\\ A\neq\Phi\\ A\neq\Theta}}\ \sum_{A_i\cap B_j\cap C_l\cap\ldots=A} pt\cdot m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)\ldots\Big]$$

$$+\sum_{A_i\cap B_j\cap C_l\cap\ldots=\Theta}\frac{|\Theta|}{|A_i|+|B_j|+|C_l|+\ldots-|\Theta|}m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)\ldots$$

$$+k\cdot cf\cdot\sum_{i=1}^{M}(m_i(A)\cdot cre(S_i))+k(1-cf)$$

$$=\frac{1-k}{P}\Big[\sum_{A_i\cap B_j\cap C_l\cap\ldots\neq\Phi} pt\cdot m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)\ldots$$

$$+k\cdot cf\cdot\sum_{i=1}^{M}(m_i(A)\cdot cre(S_i))\Big]+k(1-cf)$$

$$=\frac{1-k}{P}\cdot P+k\cdot cf\Big[\sum_{\substack{A\subset\Theta\\ A\neq\Phi}}\sum_{i=1}^{M}(m_i(A)\cdot cre(S_i))\Big]+k\cdot(1-cf)$$

$$=1-k+k\cdot cf\Big[\sum_{i=1}^{M}(1\cdot cre(S_i))\Big]+k(1-cf)=1-k+k\cdot cf+k-k\cdot cf$$

From the above statements, we can see that evidence can be directly synthesized by the above formula and decisions can be made based on decision-making rules when evidence is in a relatively small number. It is easy to find that evidence's isolation degree in this paper is equivalent to the evidence credibility in [17] when the number of the evidence is $\boldsymbol{k}$.

Provided the amount of evidence reaches a certain level, data mining to the isolated points of evidence is employed, therefore, a new combination formula is proposed, as shown in Equation 2. And the new fusion rule 2 is showed as follow:

$$m(\Phi)=0$$

$$m(A) = \frac{1-k}{p}\cdot \sum_{A_i \cap B_j \cap C_l \cap ...=A} pt\cdot m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)..$$

$$+k\cdot cf\cdot \sum_{i=1}^{M}(m_i(A)\cdot cre(S_i))$$

$$m'(A) = \frac{1-k}{p}\cdot \sum_{A_i \cap B_j \cap C_l \cap ...=A} pt\cdot m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_l)..$$

$$+k\cdot cf\cdot \sum_{i=1}^{M}(m_i(A)\cdot cre(S_i))$$

$$m(\Theta) = \frac{1-k}{p}\cdot \sum_{A_i \cap B_j \cap C_l \cap ...=\Theta} \frac{|\Theta|\cdot(m1(A_i)\cdot m2(B_j)\cdot m3(C_l)...)}{|A_i|+|B_j|+|C_l|+...-|\Theta|}$$

$$+k(1-cf)+\sum_{i=1}^{n}(m(A_i)-m'(A_i))+k\cdot cf\cdot \sum_{i=1}^{M}(m_i(\Theta)\cdot cre(s_i))$$

Obviously, formula 2 comes out when some adjustments of formula 1 is done. Through the prove to formula 1, it is similar for the formula 2. Where, *m(A)* expresses the post-combination probability of all the evidence, *m'(A)* indicates the post-combination probability of the evidence collection after deleting some evidence with low credit. With the premise of new synthesis formula, we know that after data mining to isolated points, we can circulate their probability after their integration with others and distribute and add them to the uncertain focal element Θ, that is, the evidence of low credit that can not provide reasonable and useful information.

Aided by the above mentioned formula, we can integrate several evidence into one and obtain a group of basic probability assignment function values of the focal elements containing decision-making information. A non-deterministic action A was likely to bring a outcome state $result_i(A)$ in decision-making, where the index i ranged within the number of different results. Prior to the implementation of action A, the expert gives the probability $P(result_i(A)|Do(A),E)$ for each result, in which E represents the integrated evidence. *Do(A)* indicates the execution of proposition A under the current state, then given the evidence, using the following formula , we can calculate the expected utility of the operation *EU(A|E)* in formula (7):

$$EU(A|E)=\sum_{i}(p(result_i(A)|Do(A),E)\cdot u(result_i(A))) \quad (7)$$

Where, *U(Result i(A))* indicates the utility values of the decision-making with this outcome. We can design evaluation function to evaluate the results, like the formula (8) as follows:

$$F(A)=m(A)\cdot EU(A|E) \quad (8)$$

When probability is identical, the higher the EU is, the better the results of the decision-making relatively will be. Similarly, when EU is the same, preference for the decision-making action of relatively has larger probability. A rational decision-making should choose the action which can maximize the evaluation function after each selection of decision-making with a corresponding of adjustment or update to $P(result_i(A)|Do(A),E)$.

V. EXPERIMENT AND ANALYSIS

The experimental data is mainly to verify the validity and reliability of the combination formulas presented in this paper. As the accuracy, reliability of the final synthesis and decisions generated according to decision-making rules can be ensured when the combination of the formula is correct.

A. Experimental data of the combination formula

After data is mined of the isolated point within evidence and in order to show the fusion effect of the application of new combination formula to the integration rules, we cite examples in [16,20]. To compare the results with the previous one, in the application process of the following examples, the conflict information can be fully utilized, that is $\boldsymbol{cf}$ = 1. The following two examples are based on the formula 1 with a calculated result.

Example 1

To identification-based framework $\Theta=\{a,b,c\}$, the evidence source is :

$$s_1: m_1(A)=0.98, m_1(B)=0.01, m_1(C)=0.01$$
$$s_2: m_2(A)=0, m_2(B)=0.01, m_2(C)=0.99$$
$$s_3: m_3(A)=0.9, m_3(B)=0, m_3(C)=0.1$$
$$s_4: m_4(A)=0.9, m_4(B)=0, m_4(C)=0.1$$

To consider data experiments 1 with full utility of conflict information, we use the D-S synthetic formula, Yager formula, rules from [16,17,21], and the rules in this paper, the fusion results are shown in Table 1:

Example 2

To consider two evidence sources with consistence:

$$\Theta=\{a,b,c,d,e,f,g,h\},$$

$$s1: m1(a)=0.5, m1(a,b,c)=0.4, m1(a,b,c,d,e,f,g,h)=0.1$$

$$s2: m2(a,b)=0.3, m2(a,b,c,d,e)=0.5, m2(a,b,c,d,e,f,g,h)=0.2$$

We use D-S formula, Yager formula, the rules from [16,17,21,22] and the rules in this paper, the integration results are listed as follows. By calculating we can see the overall conflict ***K = 0*** for the total evidence source, the fusion results are shown in Table 2.

B. Analysis

Synthesis formula in D-S evidence theory is the simplest one. But when the total conflict between the evidence is up to 1, it can hardly be put to use and the normalized results do not perform very well. Yager formula doesn't adopt the normalization factor, however it can pass all the conflict information to the identification framework, in the case of the vast majority of the evidence.

Table1 comparison of synthesis rules

Formula rules	M(A)	M(B)	M(C)	M(Θ)
D-S formula	0	0.01	0.99	0
Yager formular	0	0.001	0.0099	0.99
[4] rule	0.4851	0.01	0.5049	0
[7] rule	0.4851	0.01	0.5049	0
new rule	0.4851	0.01	0.5049	0
D-S formula	0	0	1	0
Yager formula	0	0	0.00099	0.99901
[4] rule	0.626	0.0067	0.3673	0
[7] rule	0.881	0.0051	0.1063	0
new rule	0.786	0.0055	0.2085	0
D-S formula	0	0	1	0
Yager formula	0	0	0.000099	0.999901
[4] rule	0.6949	0.005	0.3001	0
[7] rule	0.8903	0.0034	0.1139	0
new rule	0.8551	0.0035	0.1414	0

Table 2 comparison of synthesis rules

Synthetic rules	m(a)	m(a,b)	m(a,b,c)	m(a,b,c,d,e)	m(a,b,c,d,e,f,g,h)
d-s rule	0.5	0.15	0.28	0.05	0.02
yagerrule	0.5	0.15	0.28	0.05	0.02
[2] rule	0.5	0.15	0.28	0.05	0.02
[4] rule	0.5	0.15	0.28	0.05	0.02
[10]rule	0.5	0.15	0.28	0.05	0.02
[7]rule	0.323	0.2053	0.3519	0.0733	0.047
new rule	0.325	0.20527	0.3517	0.07327	0.046

Data experiment 1 in table 1 shows that the improved rule proposed in this paper runs faster than the D-S formula, Yager formula and the formula from [22] in converging to the consistent information, and serves decision-makers better. After the entry of the evidence source S4, then *m(A)= 0.8551*, the level of support for A will be over 75%, which can help make a more credible decision. After joining with S4, since originally, *m(C)=0.2085*, while m*(C)=0.1* in S4,the synthesis value of *m(C)* should be between 0.1 and 0.2085, the table 1 shows the final result of *m(C)* is 0.1414, which is much more reliable, compared with the result in [17], after the join of *S4*, which has relatively negative impact on C's distribution, the ratio of C's allocation actually is increased and is more reliable.

Data experiment 2 shows that several synthesis rules, in which the previous ones are of the same result, the integration results m(a) in the paper are smaller than them of other five ones, but the rest focal elements' probability distribution are larger than the other five, this is because we take into account of their cross extent(the weight) in the process of cross-integration among the evidence source. Through *m1(a)*=0.5 to evidence 1 and *m2(a,b)=0.3* to evidence 2 , we can predict that *m(a)* should be between 0.3 and 0.5, only the rules in this paper and in [17] are consistent with this prediction.

VI.CONCLUSION

In this paper the D-S Evidence Theory and Isolated Points Mining are firstly introduced, then the synthesis formula from D-S evidence theory is expended, which is applied into decision-making fusion system, that is, the probability of conflict in evidence is allocated with weight value according to the average level of support, then the various decision-making information are fused, a new decision-making method is obtained. At the same time, in the case of large quantity of evidence source, Isolated Points

Mining to the evidence waiting for being integrated is applied, and the isolation extent for simulating the reliability is used, which enhances the reliability and rationality of the synthesis results.

From the experimental results, it's clear that the new synthesis method is not only effective and works well to the evidence of a high level of conflict but also applicable to decision-making fusion. Because this paper involves a great breadth and diversity, a lot of empirical evidence is still in need. The synthesis formulas of evidence theory in decision-making method of this paper is mainly to improve the results, how to focus on their efficiency and reduce the consumption of synthesis, and how to reduce the impact when aberrant results occur after evidence data mining, will be something to improve in the future work.

ACKNOWLEDGEMENTS

This work is supported by grants from the the National Natural Science Foundation of China (No. 60774033) and Specialized Research Fund for the Doctoral Program of Higher Education of China (No. 20070384003 and 20090121110022). The author would also acknowledge the support provided by Program for New Century Excellent Talents in Fujian Province University, the Industrial Technology Special Project of Development and Reform Committee in Fujian Province of China(2007[875]) and the 2008 Foundation of Project of Science & Technology in Xiamen (3502Z20081098).

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