Springer

Journal of Mechanical Science and Technology

Journal of Mechanical Science and Technology 22 (2008) 2417~2425

www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-008-0801-2

Improved information fusion approach based on D-S evidence theory †

Rui Sun, Hong-Zhong Huang* and Qiang Miao

School of Mechatronics Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, 610054, China

(Manuscript Received February 12, 2008; Revised July 13, 2008; Accepted August 1, 2008)

Abstract

Conventional D-S evidence theory has an unavoidable disadvantage in that it will give counter-intuitive result when fusing high conflict information. This paper proposes an improved method to solve this problem. By reassigning weight factors before fusing, the method can give reasonable results especially when the initial weight factors of conflict evidences are almost equal. It gives an adjustable factor to adjust the reassigning force. An example is given to illustrate these advantages.

Keywords: D-S evidence theory; Information fusion; Weight factor reassignment

1. Introduction

With the increased demand for machine safety and reliability, machine fault detection and diagnosis plays a more and more important role in engineering practice. Due to the increasing of machine complexity, it is not suitable for machine condition monitoring by a single sensor. The use of multi-sensors or sensor array becomes widespread. New challenges have arisen with regard to making more reasonable inferences based on multi-source information.

D-S evidence theory is regarded as an efficient method for information fusion. The large number of researches that have been done can be divided in two categories: (1) proposing an improved algorithm for information fusion, and (2) the engineering practice with the algorithm.

In the early research, evidences were thought 100 percent reliable, so different evidences have the same powerful contribution to the fusion result. Later researchers thought about the difference of evidence reliability, which came from the imprecision of signal collection, data processing and feature extraction. In information fusion, weight factors have been added to represent these differences. However, many researchers did not take one important factor into account, which is the evidence support level. In engineering practice the information of multi-sensors may not point to one single fault. Different sensor information may have different support levels to one special fault; the difference may come from the detect principle.

Fusing information from multi-sources with evidence theory and providing the ultimate result for the decision-making is in the fuzzy category. Numerical computation ignores this fuzziness on some level. Fan pointed out a feasible approach to turning fuzzy sensor information into precision BPAs (basic probability assignments) with the use of trapezoidal/semi-trapezoidal fuzzy number [1]. The weight factors, which represent the importance of different evidences, are assigned by three ways: (1) assign subjectively; (2) assign by the expert's knowledge; and (3) assign by the statistic. Assigning subjectively is not reasonable and used only in a lack of system knowledge. Assigning by the expert's knowledge face two main shortcomings: (1) the expert's knowledge may be limited or imprecise; and (2) the expert's knowledge

† This paper was recommended for publication in revised form by Associate Editor Eung-Soo Shin

*Corresponding author. Tel.: +86 28 83206916, Fax.: +86 28 83206916
E-mail address: hzhuang@uestc.edu.cn

may be hard to be transform into the right form that can be used in information fusion with evidence theory. Assigning by statistics is appropriate for representing the fuzziness, but we always face the deficiency of statistics on the initial running stage of new equipment.

Artificial Neural Network (ANN) has specific superiority over other conventional methods in dealing with a multi-input multi-output nonlinear system. This advantage is due to the ability of self-learning. Some researchers combined evidence theory with ANN to solve problems, and achieved some results. In this paper we do not want to repeat other researchers' experience, and refer to this self-learning ability here as this is helpful to handle the fuzziness in information fusion and decision making.

The detailed process is described below. Information from multi-sensors is fused with initial weight factors. In the fusing algorithm factor α is equal to 1, which represents the weight factor reassignment force, and more details will be given in section 3. The fusion result is evaluated with an expert's experience and the result of the other information fusion method. Then factor α and initial weight factors will be modified according to the evaluation result. After a period of training, the fusion system can undertake tasks by itself. There is another way to train so the system designer can give some samples to the system, which includes multi-sensor information and diagnosis results. The fusion system reach the sample gradually by modifying factor α and initial weight factors.

In this paper we have proposed a new method based on D-S evidence theory that can increase the rationality through a reassigning weight factor, which has self-learning ability by adjusting factor α. The rest of the paper is organized as below. Section 2 introduces D-S evidence theory and its disadvantages. Section 3 proposes a new method of information fusion based on D-S evidence theory through a reassigning weight factor. An example to validate the proposed new method and system is delivered. A summary and conclusions are given at the end of the paper.

2. Evidence theory

2.1 Basic concepts

Θ is a finite nonempty set of mutually exclusive alternatives, which is called the frame of discernment (Shafer, 1976). This frame of discernment contains every possible hypothesis. For example $\Theta = \{F_1, F_2, \cdots, F_n\}$, F_1 is the hypothesis of "F_1 is present". The task of D-S evidence theory is to evaluate the strength of belief in each hypothesis.

BPAs is a function, $m: 2^\Theta \rightarrow [0.1]$, $m(\phi) = 0$, $\sum_{X \subseteq \Theta} m(X) = 1$. That is, when a piece of evidence is given, the belief level between [0,1] should be assigned to each possible hypothesis or their combination, the empty set should assign zero believe level and all the BPAs should add up to one.

Assuming $\Theta = \{F_1, F_2, F_3, F_2F_3\}$, $m(\{F_1\}) = 0.5$, $m(\{F_2\}) = 0.2$, $m(\{F_2F_3\}) = 0.3$, this evidence tell us that F_1, F_2, $\{F_2, F_3\}$ are present and have belief levels of 50%, 20% and 30%, respectively.

In information fusion there are two functions to represent the belief levels in the ultimate result: $Bel(X)$ and $Pl(X)$. $Bel(X)$ represents the total belief level. This is defined as,

$$Bel(X) = \sum_{Y \subseteq X} m(Y) \qquad \forall X \subseteq \Theta \tag{1}$$

$Pl(X)$ represents the plausibility belief level, which is defined as

$$Pl(X) = \sum_{X \cap Y \neq \phi} m(Y) \qquad \forall X \subseteq \Theta, Y \subseteq \Theta \tag{2}$$

For example, if $\Theta = \{F_1, F_2, F_3\}$, then

$$Bel(F_1) = m(F_1)$$
$$Pl(F_1) = m(\{F_1\}) + m(\{F_1, F_2\}) + m(\{F_1, F_3\}) + m(\Theta)$$

Obviously, $Bel(X)$ and $Pl(X)$ have the relationship

$$Pl(X) \geq Bel(X) \qquad Pl(X) = 1 - Bel(\overline{X}) \tag{3}$$

$Bel(X)$ and $Pl(X)$ are the lower and the upper limits of the belief level of hypothesis X, respectively. $[Bel(X), Pl(X)]$ is the confidence interval which describes the uncertainty of X. If the interval increases, that is to say some information in fusion is missing or unreliable.

In fusion, we can use $Bel(X)$ or $Pl(X)$ or the interval to represent the belief level of hypothesis. Multiple evidences can be fused by using Dempster's combination rule:

$$m(C) = m_i(X) \oplus m_j(Y)$$
$$= \begin{cases} 0 & X \cap Y = \phi \\ \dfrac{\sum_{X \cap Y = C, \forall X, Y \subseteq \Theta} m_i(x) \times m_j(Y)}{1 - \sum_{X \cap Y = \phi, \forall X, Y \subseteq \Theta} m_i(x) \times m_j(Y)}, & X \cap Y \neq \phi \\ & i, j = 1, 2, \cdots, m \end{cases} \tag{4}$$

The combination rule has two important mathematical properties, commutativity and associativity. We illustrate these two properties with the following equations:

$$m_i \oplus m_j = m_j \oplus m_i$$
$$(m_i \oplus m_j) \oplus m_k = m_i \oplus (m_j \oplus m_k) \tag{5}$$

If we should get a result by fusing multiple evidences, there is no need to think about the fusing order. These properties provide a convenience to evidence pretreatment such as a similar grouping.

2.2 Main disadvantage and current focus

The conventional method of D-S evidence theory has unavoidable disadvantages. With high conflict evidence fusion using the conventional method, the result will be counter-intuitive. There is a typical example given by Zadeh (1986) to describe this disadvantage. Consider a situation in which we have two belief structures m_1 and m_2:

$$m_1(a) = 0.9, m_1(b) = 0.1, m_2(b) = 0.1, m_2(c) = 0.9$$

The fusion result is $m(a) = m(c) = 0, m(b) = 1$. We can find m_1 and m_2 have low support level to hypothesis b, but b is totally believed in the fusion result. m_1 and m_2 have high support level to hypotheses a and c, respectively, but a and c are totally unbelievable in the fusion result.

The reason of this counter-intuition is that a conventional combination rule cannot handle high conflict evidences. To solve this problem, some research has been done and several improved methods based on the D-S evidence method have been proposed.

Yager improved D-S evidence theory by classifying the conflicting evidences into set Θ (Yager,1987). Though conflicts are removed, some useful information is also lost. When the conflict level is high a large number of beliefs are assigned to set Θ, that is, many fields are unknown, which is useless for decision making. Smets proposed a TBM model (1994) in which the existence of evidence conflict is due to the incompletion of the frame of discernment, and the belief of conflict should be assigned to set Θ.

Other researchers do not agree to assigning the conflict to set Θ. Evidence conflicts did not indicate our ignorance of discernment. The conflict includes some useful information to support the decision making, so they suggest to assign the conflict factor to possible hypotheses all or partly.

Murphy proposed an average rule of combination (2000). The rule is to average all the BPAs to get new BPAs. This combination rule is simple, but in some situations simple averaging cannot give the belief difference of a hypothesis. In some situations, this cannot give a useful result for decision making.

The conflict belief reassignment method can be classified in two main categories: (1) assigning the belief of conflict to all possible hypotheses equally by ignoring the evidence differences. This average assignment method is obviously unreasonable. Thinking about this shortcoming, some researchers proposed an improved assignment method. (2) Assigning the belief of conflict according to the evidence difference. If one evidence is more important than other evidences in fusion, it should be assigned with more belief in this method. The second method is obviously more reasonable than the first one, but these assignments are all posteriori processes and are passive modifications. In this paper, we propose a positive method to handle the evidence conflict. Before fusion we assign the weight factor according to the conflict level, and fuse information with the new evidence weight factor. This method can avoid the imprecision in BPAs and initial weight factor assignment, and the fusion result can reach the optimal result on some level.

3. Improved information fusion approach

In the research field of improving information fusion algorithm, the main problem is how to handle the high conflict evidences.

Fan and Zuo (2006) have given the hypothesis that different evidences have different support levels for different faults. For one group of evidences, we should assign the weight factor multiple times due to different fault hypotheses, compare the conclusions under different hypotheses and get the most possible conclusion. We know in practical application that the evidences chosen by the designer should point to one group of fault hypotheses of one special equipment which may be in different types. The support levels of these evidences should be stable almost. Weight factors should be modified only in the case of evidence conflict, in which some information in fusion is unbelievable on some level. Unbelievable information should come from sensor fault, environmental influence, system parameters unordered variations, etc.

When a single or a small part of evidence has high conflict with most of the other evidences in fusion, this or these evidences' weight factors should be modified down correspondingly. The other evidences' weight factors should be modified up to make the sum of weight factors equal to one. This method is devoted to weakening the destructive influence of "bad" information.

3.1 The conflict factors

The main theme of this improved method is the reassigning of weight factors, and the reassigning is according to the conflict factors. This conflict factor does not represent the conflict level between each pair of evidences, nor does it represent the whole conflict level of the evidence group. Each evidence has its own conflict factor that indicates the conflict level between this evidence and all others.

Generally assume the following fault hypothesis, $\Theta = \{F_1, F_2, F_3, \cdots, F_n\}$, and the following evidence set, $E = \{E_1, E_2, E_3, \cdots, E_m\} = \{m_1, m_2, m_3, \cdots, m_m\}$, which have the weight factor vector $W = \{w_1, w_2, \cdots, w_m\}$. We define the conflict factor k_i by

$$k_i = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{m} C_{ij} - \sum_{\substack{j=1 \\ j\neq i}}^{m} E_{ij}}{\sum_{\substack{j=1 \\ j\neq i}}^{m} C_{ij} + \sum_{\substack{j=1 \\ j\neq i}}^{m} E_{ij}} \tag{6}$$

where

$$C_{ij} = \sum_{\substack{p=1,q=1 \\ p\neq q}}^{n} m_i(F_p) m_j(F_q) \qquad E_{ij} = \sum_{p=q=1}^{n} m_i(F_p) m_j(F_q)$$

k_i belongs to $[-1,1]$. This k_i of evidence E_i represents the ratio between the conflict levels and conform level to all other evidences. Using k_1 instead of C_i , is to consider the prominence of conflict.

3.2 The reassignment amount of weight factor

Defining the amount of weight factor as reassignment amount is the pretreatment in the improved method. The amount represents the strong level of reassigning, obviously having great influence on the ultimate result. It is reasonable that the amount of reassignment weight factor is relevant to the conflict level. In the previous section we obtained the conflict factors k_i of each evidence, which represents the individual conflict levels and is not suitable for representing the global conflict level. We define the average conflict factor k^* by

$$k^* = \frac{1 + \frac{1}{m}\sum_{i=1}^{m} k_i}{2} \tag{7}$$

where k^* belongs to $[0,1]$. Then we can define the amount of weight factor w^* as

$$w^* = m \times (k^*)^{\alpha} \times \min\{w_i \mid i = 1, 2, \cdots, m\}$$

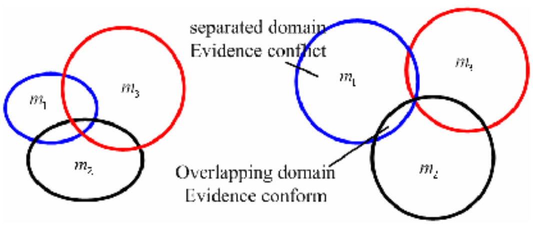
α is a decay coefficient used for the modification of the method through adjustment of the reassigning level. The default value of α is equal to one.

3.3 The reassignment principles

Now we determine the amount of weight factor w^* for reassigning. All evidences get their basic weight factor $W_b = \{w_{1b}, w_{2b}, \cdots, w_{mb}\} = \left\{w_1 - \frac{1}{m}w^*, w_2 - \frac{1}{m}w^*, \cdots, w_m - \frac{1}{m}w^*\right\}$. The reassigning of weight factors for each evidence is according to the conflict level between one evidence and the others.

Evidences E can be considered as m vectors in n -dimension vector space. Evidence conform can be considered as vectors getting close or overlapping, while evidence conflict can be considered as vectors getting departure.

Fig. 1 shows two kinds of distributions of evidence vectors in n -dimension vector space. Type (b) has no overlapping domain over three evidences and type



(a) (b)

Fig. 1. Demonstration of evidence conflicts.

(a) has overlapping domain over three or more evidences. It is possible to analyze exact distributions of all evidence vectors and their relationships, but it is unnecessary considering the algorithm efficiency. Thus we assume the precise distribution as type (b). The shortcoming of ignoring the precise distribution of evidence vectors will be covered by systems' self-learning and modification.

The reassigning of weight factor is divided into two steps: (1) assigning according to the conform factors, and (2) assigning according to the conflict factors. Correspondingly w^* is separated into two parts w_1^* and w_2^*.

$$w_1^* = \frac{\frac{1}{2}\sum_{i=1}^{m} E_i}{\frac{1}{2}\sum_{i=1}^{m} E_i + \sum_{i=1}^{m} C_i} w^*$$

$$w_2^* = \frac{\sum_{i=1}^{m} C_i}{\frac{1}{2}\sum_{i=1}^{m} E_i + \sum_{i=1}^{m} C_i} w^* \tag{8}$$

where $E_i = \sum_{j=1, j\neq i}^{m} E_{ij}$, $C_i = \sum_{j=1, j\neq i}^{m} C_{ij}$

Step1:

Compute the weight factor addition 1 w_{i1} of each evidence as follows. Current weight factor of E is W_1.

$$w_{i1} = \frac{E_i}{\sum_{i=1}^{m} E_i} w_1^* \tag{9}$$

$$W_1 = \{w_1, w_2, \cdots, w_m\}$$
$$= \{w_{1b} + w_{11}, w_{2b} + w_{21}, \cdots, w_{mb} + w_{m1}\}$$

Table 1. Evidences and BPAs.

	F_1	F_2	…	F_n	Weight factor
E_1	$m_1(F_1)$	$m_1(F_2)$	…	$m_1(F_n)$	w_1
E_2	$m_2(F_1)$	$m_2(F_2)$	…	$m_2(F_n)$	w_2
…	…	(F_2)	…	…	…
E_m	(F_1)	m_m	…	$m_m(F_n)$	w_m
	m_m				

Table 2. BPAs modification.

	F1	F2	…	Fn	Θ
E_1	$m_1'(F_1)$	$m_1'(F_2)$	…	$m_1'(F_n)$	$1-w_1/w_{\max}$
E_2	$m_2'(F_1)$	$m_2'(F_2)$	…	$m_2'(F_n)$	$1-w_2/w_{\max}$
…	…		…	…	…
E_m	$m_m'(F_1)$	$m_m'(F_2)$	…	$m_m'(F_n)$	$1-w_m/w_{\max}$

Step2:

Compute the weight factor addition 2 w_{i2} of each evidence. Current weight factor of E is W_2.

$$w_{i2} = \frac{\frac{1}{C_i}}{\sum_{i=1}^{m}\frac{1}{C_i}} w_2^* \tag{10}$$

$$W_2 = \{w_1, w_2, \cdots, w_m\}$$
$$= \{w_{1b} + w_{11} + w_{12}, w_{2b} + w_{21} + w_{22}, \cdots, w_{mb} + w_{m1} + w_{m2}\}$$

W_2 is the ultimate weight factor distribution, which is used for information fusion in the next section.

3.4 Information fusion process

We fuse these evidences with the ultimate weight factors. The fusing procedure is referred to Fan (2005), which is briefly introduced here.

Assume a fusing procedure with m evidences and n hypotheses as Table 1.

Modify BPAs with the relative weight factors as Table 2.

where $m_m{}'(F_n) = m_m(F_n) \times \frac{w_m}{w_{\max}}$

After the modification of the probability assignments, all evidences have the same importance in the fusion. We can fuse them using Eq.(11).

$$m(C) = m_{i,\bullet}(X) \oplus m_{i',\bullet}(Y)$$
$$= \begin{cases} 0 & X \cap Y = \phi \\ \dfrac{\sum_{X \cap Y = C, \forall X,Y \subseteq \Theta} m_{i,\bullet}(X) \times m_{i',\bullet}(Y)}{1 - \sum_{X \cap Y = \phi, \forall X,Y \subseteq \Theta} m_{i,\bullet}(X) \times m_{i',\bullet}(Y)} & X \cap Y \neq \phi \end{cases} \quad (11)$$

3.5 Flowchart of this improved method

The flowchart of the improved method is shown in Fig. 2. The improved method provides more reasonable results than does the conventional method, because of the reassignment. It also provides a mechanism to handle the fuzziness of BPAs or original weight assignment.

In the flowchart, we define a factor k to evaluate the globe conflict level. This factor is given before the weight factor reassignment and the fusion process. If the globe conflict level of evidences is over k, the reassignment of weight factor will be fired. If we need reassignment anyway, we could specify $k = 0$.

3.6 Numerical example

In this section, an example is given to describe the detailed process. Assume the fault hypothesis is $\Theta = \{F_1, F_2, F_3\}$ according to the machine's failure modes, and three evidences have been obtained. The BPAs of faults supported by such evidences and the weight factors are listed as

$$\begin{array}{c} \\ m_1 \\ m_2 \\ m_3 \end{array} \begin{array}{c} \begin{array}{cccc} F_1 & F_2 & F_3 & w \end{array} \\ \begin{bmatrix} 0.1 & 0.8 & 0.1 & 0.4 \\ 0.1 & 0.7 & 0.2 & 0.4 \\ 0.8 & 0.1 & 0.1 & 0.2 \end{bmatrix} \end{array}$$

After the weight factor assignment, the weight factor vector is

$$W = \{0.4161, 0.4161, 0.1678\}$$

According to the ultimate weight factor assignment, we modify the BPAs and get

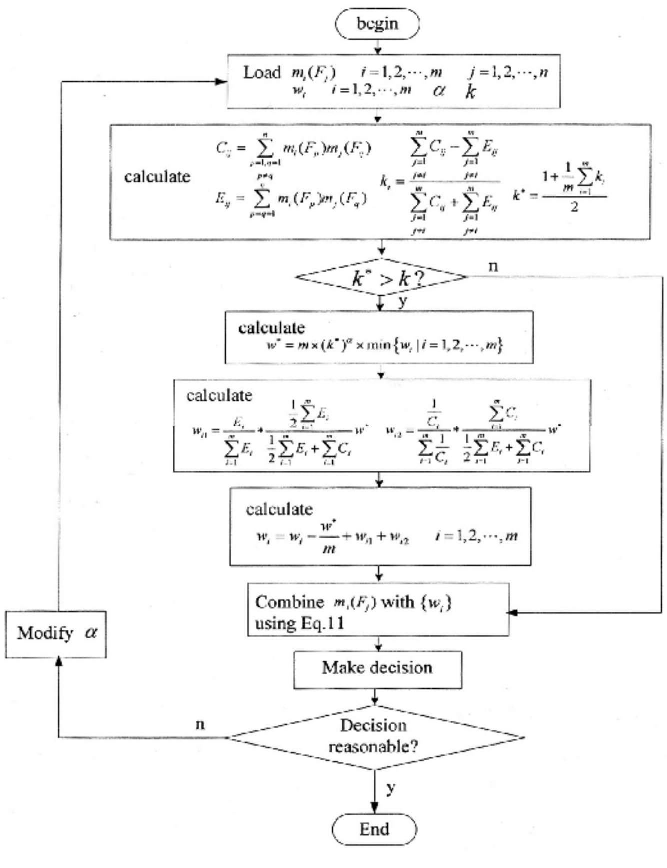


Fig. 2. flowchart of this improved method.

$$\begin{array}{c} \\ m_1 \\ m_2 \\ m_3 \end{array}\begin{array}{c} \begin{array}{cccc} F_1 & F_2 & F_3 & \Theta \end{array} \\ \begin{bmatrix} 0.1 & 0.8 & 0.1 & 0 \\ 0.1 & 0.7 & 0.2 & 0 \\ 0.32264 & 0.04033 & 0.04033 & 0.5967 \end{bmatrix} \end{array}$$

The fusing result is shown in the Table 3.

3.7 Comparison with original method

If the weight factors of evidences have conspicuous distinguishment, the conventional and improved methods have no big difference in results, which is shown in the second column of Table 4. If the weight factors of evidences get closer, the improved method can give more a reasonable result as shown in the third and fourth columns of Table 4.

Fig. 2 and Fig. 3 show the corresponding relationship between $m(F_1)$, $m(F_2)$ and the weight factor of E_1. Here we assume the weight factors of E_1 and E_2 are equal. The red curve is drawn with the conventional method, and the blue curve is drawn with the improved method. We can find that each curve has a sudden change, but the blue one changes before the red one.

Referring to the BPAs and the initial weight factor assignments, we can find the blue one is more reasonable. Evidence 1 and 2 are all support fault 1 chiefly, and evidence 3 is support fault 2. When the weight factors of these three evidences are almost equal, the result of fusion should be support to fault 1. The change of result from fault 1 supporting to fault 2

Table 3. The fusion result of example.

$m_1 \oplus m_2$	$m(F_1)$=0.0169, $m(F_2)$=0.9492, $m(F_1)$=0.0339, $m(\Theta)$=0
$m_1 \oplus m_2 \oplus m_3$	$m(F_1)$=0.0243, $m(F_2)$=0.942, $m(F_1)$=0.0336, $m(\Theta)$=0

Table 4. Comparison of conventional and improved methods.

	w_1=0.4 w_2=0.4 w_3=0.2	w_1=0.35 w_2=0.35 w_3=0.3	w_1=0.33 w_2=0.33 w_3=0.34
Conventional method	$m(F_1)$=0.0431 **$m(F_2)$=0.9239** $m(F_3)$=0.0330 $m(\Theta)$=0	$m(F_1)$=0.0588 **$m(F_2)$=0.9087** $m(F_3)$=0.0325 $m(\Theta)$=0	$m(F_1)$=0.4957 **$m(F_2)$=0.3948** $m(F_3)$=0.1095 $m(\Theta)$=0
Improved method	$m(F_1)$=0.0255 **$m(F_2)$=0.9409** $m(F_3)$=0.0336 $m(\Theta)$=0	$m(F_1)$=0.0291 **$m(F_2)$=0.9374** $m(F_3)$=0.0335 $m(\Theta)$=0	$m(F_1)$=0.0423 **$m(F_2)$=0.9247** $m(F_3)$=0.0330 $m(\Theta)$=0

supporting should happen only in a situation that weight factors of evidence 1 and 2 are all less than that of evidence 3, but the sum of evidence 1 and 2's weight factors is bigger than that of evidence 3. The difference between these two curves is related to the coefficient α.

Fig. 5 shows the corresponding relationship between coefficient α and the change interval. Different evidence status may have a different relationship, and we can adjust α to make the fusion result more reasonable.

The determination of α is by two different ways: (1) given by designers or experts according

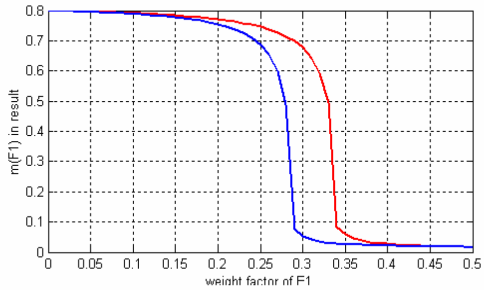


Fig. 3. The relationship between weight factor of E_1 and $m(F_1)$ in results.

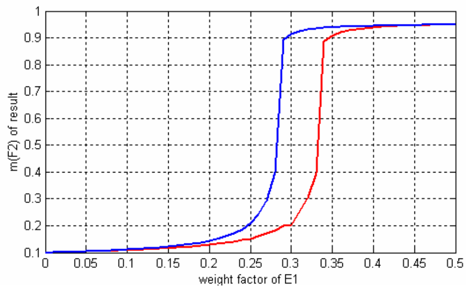


Fig. 4. The relationship between weight factor of E_1 and $m(F_2)$ in results.

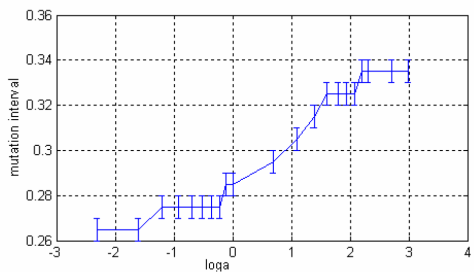


Fig. 5. The relationship between coefficient α and the change interval.

to experience or statistics, while (2) the system runs with an initial α value and adjusts it by self-learning through system running.

4. Conclusions

By weight factor reassignment, we can get a more reasonable result through information fusion, especially when the weight factors of different evidences are approximate. In this improved method, we can adjust the coefficient α to make the conclusion reasonable.

The improved method with weight factor reassignment has higher capability in distinguishing bad evidences. If an evidence is abnormal or unbelievable, it must have high conflict level with other evidences than normal. In this situation, weight factor reassignment can reduce the influence of bad evidence.

However, the improved method has one obvious disadvantage: It can only be used to fuse three evidences or more. If we have to fuse two evidences, the improved method cannot get the weight factor reassignment and cannot identify the bad evidence. The disadvantage also exists in the conventional method, which is brought from the algorithm of information fusion process, where bad evidence will have fatal influence on the result. In practical applications, we can design or choose more evidences to support the decision making in order to avoid this disadvantage.

Acknowledgments

This research was partially supported by the National Natural Science Foundation of China under the contract number 50775026, and the Specialized Research Fund for the Doctoral Program of Higher Education of China under the contract number 20060614016. Also, the constructive comments from reviewers, and the editor are very much appreciated.

References

[1] X. Fan and M. J. Zuo, 2006. Fault diagnosis of machines based on D-S evidence theory. Part 1: D-S evidence theory and its improvement. Pattern Recognition Letters. 27 (5), 366-376.

[2] X. Fan and M. J. Zuo, 2006. Fault diagnosis of machines based on D-S evidence theory. Part 2: application of the improved D-S evidence theory in gearbox fault diagnosis. Pattern Recognition Letters. 27 (5), 377-385.

[3] A. Gelman, J. B. Carlin, H. S. Stern and D. B. Rubin, 2004. Bayesian data analysis, second ed. Chapman & Hall/CRC.

[4] H. Z. Huang, 1997. Fuzzy multi-objective optimization decision-making of reliability of series system. Microelectron Reliab. 37 (3), 447-449.

[5] G. J. Klir and M. J. Wierman, 1998. Uncertainty-based information: elements of generalized information theory. Heidelberg, Physica-Verlag.

[6] C. R. Parikh, M. J. Pont and N. B. Jones, 2001. Application of Dempster–Shafer theory in condition monitoring applications: a case study. Pattern Recognition Lett. 22 (6–7), 777-785.

[7] G. Shafer, 1976. A mathematical theory of evidence. Princeton University Press, Princeton, NJ.

[8] R. R. Yager, 1987. On the Dempster–Shafer framework and new combination rules. Inf. Sci. 41 (2), 93-137.

[9] R. R. Yager, 1999. A class of fuzzy measures generated from a Dempster–Shafer belief_structure. Int. J. Intell. Syst. 14, 1239-1247.

[10] W. Liu, 2006. Analyzing the degree of conflict among belief functions. Artificial Intelligence 170, 999-924.

[11] C. K. Murphy, 2000. Combining belief functions when evidence conflicts. Decision Support Systems 29, 1-9.

[12] O. Basir and X. Yuan, 2007. Engine fault diagnosis based on multi-sensor information fusion using Dempster-Shafer evidence theory. Information Fusion 8, 379-386.

[13] A.-L. Jousselme, D. Grenier and É. Bossé, 2001. A new distance between two bodies of evidence. Information Fusion 2, 91-101.

[14] E. Lefevre, O. Colot and P. Vannoorenberghe, 2002. Belief function combination and conflict management. Information Fusion 3, 149-162.

[15] I. Bloch, 1996. Some aspects of Dempster-Shafer evidence theory for classification of multi-modality medical images taking partial volume effect into account. Pattern Recognition Letters 17, 905-919

Rui Sun, PhD candidate. He received M.E. in mechatronics engineering from University of Electronic Science and Technology of China. He is currently a Ph.D. candidate in School of Mechatronics Engineering, University of Electronic Science and Technology of China. His research interests include system reliability analysis and mechanical fault diagnosis.

Hong-Zhong Huang is a full professor and the Dean of the School of Mechanical, Electronic, and Industrial Engineering at the University of Electronic Science and Technology of China, Chengdu, Sichuan, China. He has held visiting appointments at several universities in Canada, USA, and elsewhere in Asia. He received a Ph. D. degree in Reliability Engineering from Shanghai Jiaotong University, China. His current research interests include system reliability analysis, warranty, maintenance planning and optimization, and computational intelligence in product design.

Dr. Qiang Miao obtained B.E. and M.S. degrees from Beijing University of Aeronautics and Astronautics and Ph.D. degree from University of Toronto. He is currently an associate professor of the School of Mechanical, Electronic, and Industrial Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. His current research interests include machinery condition monitoring, reliability engineering, and maintenance decision-making.