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New Method for Diagnosing a Motor with Vibration Fault

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Abstract: This study introduces a new weight-DSmT to diagnose a motor with vibration fault. DST and DSmT have something illogical in dealing with high conflicting evidences. This weight assignment method takes into account the quantity, confidence level and mutual support level of different evidences. Proportion Conflict Redistribution rule 4 based on DSmT was used to fuse. Results indicate this method advanced the basic belief assignment, although it has not been proposed in literature so far and could serve as useful method in some fusion problems.

Key words: Vibration fault, multi-source information fusion, weight assignment, dezert-smarandache theory

INTRODUCTION

In manufacturing process of modern industry, motor plays an important role. It will cause companies to incur extraordinary losses if motor breaks down. Improving operating security of motor causes general concern of academic circle. Motor is a complicated rotary machine. Vibration diagnosis occupies high range. In the process of fault diagnosis, because of the influence of environment, sensors, information processing technology and so on, Information collected from sensors is usually imprecise, uncertain and incomplete, and so this process is an uncertainty reasoning and decision-making process. Traditional methods based on single-sensor are insufficient due to the diversity and complexity of fault modes and symptoms. Dempster-Shafer Theory (DST) in information fusion has been widely used in the field of fault diagnosis because of its efficiency in dealing with uncertainty and ignorance (Smets and Kennes, 1994). But when the beliefs of sources of evidence are highly conflicting, DST fusion results are unsatisfactory. They leads to false conclusions or cannot provide a reliable result at all. To overcome these limitations , Foreign scholars such as Yager, Smets, Murphy and so on have improved the efficiency of DST to some extent (Yager, 1987, 1997; Smets, 1990, 2007). Domestic Deng *et al.* (2004) suggested a modified average method to combine belief function based on distance measures of evidence. The DSmT can be considered as a generalization of DST. Although DSmT is widely used because of its advantages in representing, measuring and combining uncertainty, the implied condition of its combination rule, which requires the frame of discernment containing all possible elements, is relatively strict. However, its fusion results sometimes has its drawback. Because the quantity, confidence level and mutual support level of different evidences are not taken into account in the frame of discernment.

THE DEZERT- SMARANDACHE THEORY

Principle of dempster-shafer theory: The definitions of frame of discernment, power set and the combination rule in DST can be easily found in the study (Shafer, 1976). We do not need to proposed in this study again. The mass distribution for all hypotheses has to fulfill the following conditions:

$$0 \le m(A_i) \le 1 \tag{1}$$

$$m(\phi) = 0 \tag{2}$$

$$\sum_{A_i \in 2^{\Theta}} m(A_i) = 1 \tag{3}$$

The belief function given by the basic probability assignment m is defined as:

$$\mathrm{Bel}(A) = \sum_{B \subset A} m(B) \tag{4}$$

The plausibility function PL indicates the total quantity. of belief that might support a hypothesis. Which is defined as:

$$\mathrm{PL}(A) = 1 - \mathrm{BEL}(\bar{A}) = \sum_{B \cap A \neq \varnothing} m(B) \tag{5}$$

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The global belief function is obtained by orthogonally combining belief function representing distinct bodies of evidence together. the Dempster's rule of combination is defined as:

$$m(A)=\begin{cases}\dfrac{\sum_{A_i\cap B_j=A} m_1(A_i)m(B_j)}{1-K} & (A\neq\varnothing)\\ 0 & (A=\varnothing)\end{cases} \tag{6}$$

$$K=\sum_{A_i\cap B_j=\varnothing} m_1(A_i)m_2(B_j)<1 \tag{7}$$

where, K is a measure of conflict between the sources and it is introduced as a normalization factor. The larger K is, the more the sources are conflicting and the less sense the combination has. Two functions can be evaluated to characterize the uncertainty about the hypotheses A.

The Dezert-Smarandache Theory and Proportion conflict redistribution rule 4: Θ is considered as a set of exhaustive and exclusive elements in DST. The frame contains all possible recognized elements.

Let $\Theta = \{\theta_1, \theta_2, ..., \theta_n\}$ be a set of n elements can potentially overlap, which is called a generalized frame of discernment. It relaxes the exclusive constraint in DST. The hyper-power set D^Θ is defined as the set of all composite hypotheses obtained from Θ with ∪ and ∩ operators such that:

- $\varnothing, \theta_1, \theta_2, ..., \theta_n \in D^\Theta$
- If A, B, $\in D^\Theta$, then $(A\cup B)\in D^\Theta$ and $(A\cap B)\in D^\Theta$
- No other elements belong to D^Θ, except those defined in 1 and 2

The generalized basic probability assignment (GBPA), generalized belief and generalized plausibility functions are compatible with the definitions in the DST because the DSmT is an extension of DST. The DSmT rule of combination of conflicting and on uncertain sources is given by:

$$m(A)=\sum_{\substack{A_1,A_2,\cdots,A_d\in D^\Theta\\ A_1\cap A_2\cap\cdots A_d=A}}\prod_{i=1}^{d} m_i(A_i) \tag{8}$$

Proportion Conflict Redistribution rules attribute conflict among sources of evidence reasonably. In this paper, we use PCR4 to combine sources with high conflict.

The PCR4 formula for the combination of two sources (s = 2) is given by: $m_{PCR4}(\varnothing) = 0$ and $\forall X\in G^\Theta/\{\varnothing\}$.

$$m_{PCR4}(X)=m_{12}(X)\left[1+\sum_{\substack{Y\in D^\Theta\\ Y\cap X=\varnothing}}\frac{m_{12}(X\cap Y)}{m_{12}(X)+m_{12}(Y)}\right] \tag{9}$$

where, m_{12} (X) and m_{12} (Y) are non-empty sets. M_{12} (X) is defined by:

$$m_{12}(X)=\sum_{\substack{X_1,X_2\in D^\Theta\\ X_1\cap X_2=X}} m_1(X_1)m_2(X_2) \tag{10}$$

If a denominator in formulas is zero, that fraction is discarded. A general formula of PCR4 for the s>2 sources has been proposed in book (Smarandache and Dezert, 2006).

A WEIGHT ASSIGNMENT METHOD BASED ON DSmT

In some cases, it is required to weight the sources of evidences which can make the target type decision objectively. Every source of evidence should be weighted considering the quantity of sources, confidence level and mutual support level of different sources. The weight factor is a measure of the importance of a source, the larger the factor is, the more important the source is. If one source is supported by others, it should be weighted a larger factor, conversely, the source should be weighted a smaller factor. If a source collide with other sources seriously, its confidence level is lower, the weight factor is smaller too. Conversely, the weight factor is larger. In this paper, sources were weighted different assignment based on quantity, confidence level and mutual support level of different sources.

The quantity of sources are taken into account fusion results, we herein define the quantity information of target focal element:

$$m_p^*(A_j)=\sum_{\substack{j=1\\ A_j\subseteq B_j}}^{N} m_p(B_j)\bullet\frac{1}{\|B_j\|}, p=1,2,\cdots,n \tag{11}$$

where, $\|B_j\|$ is the basic counting unit, A_j is the target focal element, which satisfy:

$$\sum_{j=1}^{N} m_p^*(A_j)=1$$

Mutual support level of different sources d_{pq} (A_j) is taken into account fusion results. we herein define mutual support level of sources of m_p^* and m_q^*:

$$d_{pq}(A_j)=1-m_p^*(A_j)-m_q^*(A_j) \tag{12}$$

where $p \neq q$; p, q = 1, 2, ..., N, the value of $d_{pq}(A_j)$ is the largest when two sources support absolutely, and the largest value is 1. when two sources of evidences have conflicts, $d_{pq}(A_j)<1$ and that the larger the conflict, the value gravitate towards 0 more and more.

The whole support SUP_p and crefidence CRE_p of evidences for target focal element A_j are defined as:

$$SUP_p(A_j)=\prod_{\substack{q=1\\p\neq q}}^{n} d_{pq}(A_j)\ q,p=1,2,\cdots,n,j=1,2,\cdots,N \tag{13}$$

$$CRE_p=\frac{SUP_p(A_j)}{\sum_{p=1}^{n}SUP_p(A_j)}\qquad j=1,2,\cdots,N \tag{14}$$

The crefidence CRE_p of evidence is the result of normalization SUP_p, the CRE_p value of a source of evidence reflects the weight assignment of the source.

Every target focal element of a source is weighted mean, the formula is given by:

$$m^*(A_j)=\sum_{p=1}^{N}CRE_p(A_j)\bullet m_p^*(A_j)\qquad j=1,2,\cdots N$$

Then the results are normalized, the formula is given by:

$$m(A_j)=\frac{m^*(A_j)}{\sum_{j=1}^{N}m^*(A_j)}\qquad j=1,2,\cdots N$$

DIAGNOSIS EXAMPLE BASED ON WEIGHT-DSmT

Experiment set-up: Some examples of motor rotor vibration fault diagnosis are given to illustrate the effectiveness of weight-DSmT proposed in this paper. A vibration acceleration sensor and a vibration displacement sensor are installed on sensitive sections of motor to collect trouble signal. Data acquisition system is formed. Multi-source information fusion method is used to diagnose the motor with vibration fault symptoms. Firstly, a method based on the Intrinsic Mode Functions(IMF) was used to extract the signal's energy entropy feature, Secondly, basic belief assignment function was constructed based on the output of the Back Propagation (BP) neural network; Lastly, DSmT combination rule was used to combine the different evidences and make the target type decision£. Many detailed process can be easily found in the study (Zhai *et al*., 2012), and so we do not need to include them in this paper. In order to make the elements of discernment framework typical and have lower computation cost. Let the $\Theta = \{F_1, F_2, F_3, N\}$, element F_1, F_2, F_3, N denote rotor unbalance, rotor misalignment, rotor clamping support loosening and uncertainty respectively. The generalized basic belief assignment of sources of evidences generated using the method of paper (Zhai *et al*., 2012).

Diagnosis results: In Table 1, C1 and C2 denote a vibration acceleration sensor and a vibration displacement sensor respectively. Two sensors detected one fault mode respectively. But the sources are conflicting highly. The existing DST-based fault diagnosis method can not characterize when the conflicts between the two evidences is greater than a certain threshold. DSmT combination rule is chosen to fuse the evidence. In the Table 2, in order to make the new method effectiveness clears. The classical combination fusion rule of DSmT, disjunction rule, Smets, Yager, Murphy methods and PCR4 is applied respectively. Yager's methods transfer the conflicts directly onto the uncertain term. The basic belief assignment of fault mode F_1 is 0.22, although the value is higher than the basic belief assignment of fault mode F_2. We cann't make a strategic decision only on basis of the low basic belief assignment. The basic belief assignment of fault mode F_1, F_2 and F_3 is equal based on classical combination fusion rule of DSmT, Smets and Yager methods respectively, but the conflicts are transferred to different terms. The results of PCR4 are a bit obvious. The basic belief assignment of fault mode F_1 reaches 0.539. But it reaches 0.758 based on the weight-DSmT. The unknown fault can be diagnosed by the proposed method in this paper. A total of 100 statistical experiments are made. The accurate diagnosis rate is 95%.

Table 1: Generalized basic belief assignment of evidence

Sensors	Generalized basic belief assignment of evidence
C1	$m_1(F_1) = 0.6$, $m_1(F_2) = 0.1$, $m_1(F_3) = 0.1$, $m_1(F_1 \cup F_2) = 0.2$
C2	$m_2(F_1) = 0.1$, $m_2(F_2) = 0.5$, $m_2(F_3) = 0.2$, $m_2(F_1 \cup F_2) = 0.1$

Table 2: Combination results based on multi-fusion methods

Combination method	Combination results
Classic DSm rule	$m(\varnothing) = 0$, $m(F_1) = 0.22$, $m(F_2) = 0.16$, $m(F_3) = 0.02$, $m(F_1 \cup F_2) = 0.02$, $m(F_1 \cap F_2) = 0.32$, $m(F_1 \cap F_3) = 0.14$, $m(F_2 \cap F_3) = 0.07$, $m(F_3 \cap (F_1 \cup F_2)) = 0.05$,
Disjunctive rule	$m(\varnothing) = 0$, $m(F_1) = 0.12$, $m(F_2) = 0.05$, $m(F_3) = 0.02$, $m(F_1 \cup F_2) = 0.55$, $m(F_1 \cup F_3) = 0.14$, $m(F_2 \cup F_3) = 0.07$, $m(F_1 \cup F_2 \cup F_3) = 0.05$
Yager's rule	$m(\varnothing) = 0$, $m(F_1) = 0.22$, $m(F_2) = 0.16$, $m(F_3) = 0.02$, $m(F_1 \cup F_2) = 0.6$
Murphy's rule	$m(\varnothing) = 0$, $m(F_1) = 0.52$, $m(F_2) = 0.38$, $m(F_3) = 0.05$, $m(F_1 \cup F_2) = 0.02$
Smets'srule	$m(\varnothing) = 0.58$, $m(F_1) = 0.22$, $m(F_2) = 0.16$, $m(F_3) = 0.02$, $m(F_1 \cup F_2) = 0.02$
PCR4	$m(\varnothing) = 0$, $m(F_1) = 0.539$, $m(F_2) = 0.392$, $m(F_3) = 0.049$, $m(F_1 \cup F_2) = 0.02$
Weight-DSmT in this study	$m(\varnothing) = 0$, $m(F_1) = 0.758$, $m(F_2) = 0.202$, $m(F_3) = 0.028$, $m(F_1 \cup F_2) = 0.012$

CONCLUSION

A weight-DSmT has been presented in this paper. This method have some value from theoretical point view since it takes into account the quantity, confidence level and mutual support level of different evidences. Although it has not been proposed in literature so far could serve as useful alternative. It may hopefully appear as good enough in some specific fusion problems.

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