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Fault Diagnosis of Engine Using Information Fusion Based on Dempster-Shafer Theory

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ABSTRACT

A data fusion fault diagnosis method of engine based on D-S evidential theory is presented. Firstly by extracting fault-reveling engine component from multiple sensors, such as vibration and temperature, the mass function assignment of sensors to engine component is gotten respectively, then the fusion mass function assignment is gotten by using D-S rule, lastly fault mode is found based on fusion data. Within this framework we propose weight normalization and basic probability assignments for fusion mass function assignment. Finally, we report a case study to show the efficacy of engine fault diagnosis.

Keywords: D-S evidential theory, mass function, Data fusion, Fault diagnosis

1. INTRODUCTION

In analog engine fault diagnosis, according to the different stages of testing process, the method of the fault diagnosis revolves around two main questions [1,2,3]:
(1) How to acquire precise and reliable information cues about potential faults by incorporating complementary, and possibly redundant, multiple sensors.
(2) How to fuse decisions that are derived based on multi- sensor data, which can be imprecise, and conflicting [4]. There is no single sensor that can reliably obtain all the information required for fault diagnosis. With the development of sensor technology and signal processing methods, a great deal of information can be obtained. New challenges have arisen with regard to making more reasonable inferences based on multi-source information. The information fusion technique has attracted increasing attention to fault diagnosis and structural damage detection due to its inherent capabilities in extracting information from different sources and integrating them into a consistent.

Bayesian inference can be used to update the probability of a hypothesis given a piece of observed information. This property makes possible multi-source information fusion. For details on Bayesian inference readers can refer to [5]. Though Bayesian inference can be employed to determine the probability of a decisions correctness based on prior information, it has some disadvantages: (1) the knowledge required to generate the prior probability distributions may not be available; (2) instabilities may occur when conflicting data is presented and/or the number of unknown propositions is large compared to the known propositions [6]; (3) information available to the decision-maker must be characterized by a specific distribution or an exact assertion of the truth of a proposition; and (4) it offers little opportunity to express incomplete information or partial belief [7]. Based on Dempsters research, Shafer (1976) proposed Dempster–Shafer (D–S) evidence theory as an alternative to Bayesian inference. D–S evidence theory can be considered to be a general extension of Bayesian theory and can robustly deal with incomplete data [8].

Dromigny and Zhu [9] used the Bayesian fusion technique to improve the dynamic range of a real- time X-ray imaging system by combining information acquired under two different acquisition conditions. Lucas [10] combined the probabilistic reasoning offered by a Bayesian network and logical reasoning to minimize decision uncertainty of fault diagnosis. Beck [11] used the Bayesian inference to identify the system parameters of structures.

As an extension to probability theory, the D–S evidence theory is frequently used as a method for dealing with uncertain information. Parikh et al. [12] used the D–S evidence theory to combine the outputs of two or more primary classifiers to improve overall classification performance. Kaftandjian et al. [13] described how evidence theory and fuzzy set theory were combined to improve the detection quality of weld defects. Basir and Yuan [4] used the D–S evidence theory to integrate multi- sensor information including vibration, sound, pressure and temperature to detect and identify engine faults. Fan and Zuo [8,14] improved the conventional D–S evidence theory by using fuzzy membership to detect fault in machines. Yang and Kim [15] presented an approach for fault diagnosis of induction motors based on D–S evidence theory. Zhang [16] presented an online

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fault diagnosis method through information fusion in multiple neural networks. Li and Bao [17] presented a method to locate the structure damage by integration of BP neural networks and D–S evidence theory. Guo [18] used the information fusion techniques to detect the damage of a two-dimensional truss structure and compared the damage detection accuracy of three main fusion approaches, including Bayesian fusion, D–S evidence theory and the fuzzy fusion method. The numerical results indicated that the D–S evidence theory is the most effective fusion method amongst the three fusion methods. Guo and Zhang [19] used the D–S evidence theory to identify multiple damage locations of a structure. Multiple evidences from different sources of different importance or reliability do not identically contribute to the damage detection when they are combined using D–S evidence theory. Consequently, a weighted balance evidence theory was proposed to solve this problem. Bao et al. [20] proposed a D–S evidence theory-based structural damage detect ion method by combining both global and local responses. The damage decision made from measurement of strain gauges was regarded as an information source and then combined with global information by D–S evidence theory.

In this paper we approach the fault diagnosis problem in engine components using multi-sensor measurements, vibration and temperature. We view each sensor measurement as a piece of evidence that reveals some information about the state of the engine. The Dempster–Shafer theory is used to associate multi-sensor data to engine quality indices. The paper is organized as follows. In section 2, we introduce some preliminary concepts of the evidence theory. In section 3, new schemes for weight normalization and basic probability assignments are proposed. The original ER approach is further developed to enhance the process of information fusion for engine components fault with uncertainty. The weights for fusion mass function assignment based on the distances between all sensor measurements and all fault modes can be captured. Section 4 is discussion on fault diagnosis results. Section 5 describes a numerical result of the proposed fault detection approach and to show the efficacy of engine fault diagnosis. Section 5 provides some concluding remarks.

2 EVIDENCE THEORY

2 .1 Preliminary notions of the evidence theory

Evidence Theory was initially introduced by Dempster (1967), and then Shafer (1976) showed the benefits of belief functions for modeling uncertain knowledge. In this section, some mathematical elements of Evidence Theory are recalled.

2 .2 Belief and plausibility functions:

Let $\theta=\{A_1, A_2, \ldots, A_N\}$ be a frame of discernment, in which all elements are assumed to be mutually exclusive and exhaustive. The power set of θ is denoted by $2^\theta=\{A \mid A\subseteq\theta\}$ Basic Probability Assignment (BPA) or mass function is a function that can be mathematically defined by 2^θ in $[0,1]$, such that, $m(\phi)=0$ where, ϕ denotes an empty set, and $\sum_{A\subseteq\theta} m(A)=1$. The belief function (Bel) and the plausibility function (Pl) are defined as follows:

$$
\begin{aligned}
Bel(A) &= \sum_{\phi \neq B \subseteq A} m(B) \qquad \forall A\subseteq\theta \\
Pl(A) &= \sum_{B \cap A \neq \phi} m(B) \qquad \forall A\subseteq\theta
\end{aligned}
\tag{1}
$$

in which $Bel(A)$ represents the sum of masses in all subsets of A , whereas, $Pl(A)$ corresponds to the sum of masses committed to those subsets which don't discredit A .

2 .3 Rules of evidence combination

Multiple evidences can be fused by using Dempster's combination rules, shown in equation (2), which also is known as the orthogonal sum. This sum is both commutative and associative.

$$
\begin{aligned}
m(\phi) &= 0 \\
m(A) &= \frac{1}{1-k} \sum_{B\cap C = A} m_1(B)\cdot m_2(C)
\end{aligned}
\tag{2}
$$

with

$$k = \sum_{B \cap C = \phi} m_1(B) \cdot m_2(C) > 0 \tag{3}$$

where the term k is called the conflict factor between two evidences, which reflects the conflict degree between them.

Generally speaking, for n mass functions m in θ, the measure of conflict k gives as:

$$k = \sum_{\bigcap_{i=1}^{n} E_i = \Phi} m_1(E_1) \cdot m_2(E_2) \cdot \ldots \cdot m(E_n) > 0 \tag{4}$$

and the mass function after combination is

$$m(A) = (m_1 \oplus m_2 \oplus \ldots m_n)(A) = \frac{1}{1-k} \sum_{\bigcap_{i=1}^{n} E_i = A} m_1(E_1) \cdot m_2(E_2) \ldots m_n(E_n) \tag{5}$$

3 MULTI-SENSOR DATA FUSION ALGORITHM

3.1 Data fusion algorithm

The algorithm-based approach is to select an appropriate mass function as the reliability growth model in advance, then use evidential reasoning algorithm to assessment fault diagnosis. The ER approach has been applied to decision problems in engineering design, safety and risk assessment, organizational self-assessment, and supplier assessment, e.g., motor-cycle assessment [21]. ER algorithm that satisfies several common sense rules governing any approximate reasoning based aggregation procedures [22,23].

When applying the D-S evidential theory to multi-sensor data fusion [24,25], data gotten from sensor is the theory's evidence, and it constitutes the mass function assignment of the object mode needed to be tested, represents the reliable degree of each object mode hypothesis, and each sensor forms a evident group. As far as multi-sensor data fusion is concerned, according to D-S rule, it units several evident groups to form a new comprehensive evident group. That is to say, we can use D-S rule to unite comprehensive and precise information for judging object mode. This process is briefly described as the following to generate an overall assessment by aggregating subjective judgments.

3.2 mass function assignment of the object mode hypothesis

A key problem in Dempster–Shafer evidence algorithm is the calculation of the mass function for the object mode hypothesis based on the information provided by the sources of information (e.g., sensors), once the frame of discernment is established. Assuming N_c types of faults, and M sensors, and for the sake of simplicity, suppose that all faults are independent of one another, and only one fault may occur in any given time. Let E represents the state of the engine, denoted by $E = \lfloor e_1, e_2, \ldots, e_{N_c} \rfloor$. e_i is the i th component that describes an aspect of the engine state; N_c is the number of object mode hypothesis. These are extracted from the information provided by the sensors. For example, e_1 may represent the signal acquired from a vibration sensor. Another component e_2 may represent the temperature acquired from the same sensor. Here we should take the affect of object mode number into consideration when decide the mass function assignment:

Let $m_j(e_i)$ be a basic probability mass representing the degree to which the i th engine component e_i, is assessed by j th sensor. $m_j(e_i)$ is calculated as follows:

$$m_j(e_i) = w_i \beta_j(e_i) \qquad i = 1, \ldots, N_c \quad j = 1, \ldots, M \tag{6}$$

where w_i is the weight vector that reflects the capability of sensor and $\beta_j(e_i)$ is the degree of belief for sensor j that assesses the component e_i to detect information.

Definition:

$$\alpha_j = \max\{C_j(e_i)\} \qquad i = 1,2,\cdots,N_c \tag{7}$$

$$\gamma_j = \left\{ N_c \lambda_j / \sum_{i=1}^{N_c} \{C_j(e_i) - 1\} \right\} / [N_c - 1] \qquad N_c \ge 2 \tag{8}$$

$$R_j = (\lambda_j \alpha_j \beta_j) \Big/ (\sum_{K=1}^{M} (\lambda_j \alpha_j \beta_j)) \qquad K = 1,2,\cdots,M \tag{9}$$

then the degree of belief $\beta_j(e_i)$ that sensor j is relevant to object mode e_i ($i = 1,2,...,N_c$) is:

$$\beta_j(e_i) = C_j(e_i) / \left\{ \sum_{i=1}^{N_c} C_j(e_i) + N(1 - R_j)(1 - \lambda_i \alpha_j \gamma_j) \right\} \tag{10}$$

$C_j(e_i)$ represents the measured value of sensor j to component (object mode) e_i, N_c represent the object mode number, M represent the total number of sensor, λ_j represents the certain coefficient of sensor j. It shows the measure of certainty for sensor j that provided the information for engine components and its value domain is $[0,1]$. α_j represents the maximal measured value of sensor j. γ_j represent the relevant allocation value of sensor j, R_j represents the reliable coefficient of sensor j. Then the degree of belief $\beta_j(e_i)$ of sensor j, is assessed to the component e_i, can be calculated.

Let $m_{H,i}$ be the remaining probability mass unassigned to each component e_i, $m_{H,i}$ is calculated as follows:

$$m_H(e_i) = 1 - \sum_{j=1}^{N_c} m_j(e_i) = 1 - \sum_{j=1}^{N_c} w_i \beta_j(e_i) \qquad i = 1,\ldots,N_c \tag{11}$$

3.3 Proposed Weighting Method

Sensors vary in their ability to detect information that is relevant to the fault detection task. Differences in ability can be attributed to factors such as mounting variation as well as sensitivity. For example, when two vibration sensors are used to detect valve and bearing faults of an engine, one sensor can be mounted to the valve cover, the other sensor can be attached to a bearing seat. It is obvious that the first sensor is more sensitive to the valve condition than the bearing condition. However, the second sensor is expected to be more sensitive to the bearing condition than to the valve condition. To account for this aspect the mass function provided by each sensor should be weighted so as to reflect the relative detection capability of the sensor [14]. The proposed weighting can be obtained for fusion mass function assignment based on the distances between each sensor measurements and all fault modes can be captured in engine.

Let $E = \lfloor e_1, e_2, \ldots, e_{N_c} \rfloor$, E represents the component of the engine; e_i is the i th component that describes an aspect of the each engine quality; N_c is the number of components . These components are extracted from the information provided by the sensors. Thus, for N_c object mode (or component), the engine condition can be described by a vector E_j :

$$E_j = \lfloor e_{j1}, e_{j2}, \ldots, e_{jM} \rfloor \qquad j = 1,2,\ldots,N_c$$

E_j is a component vector describing the j th fault mode and e_{jk} is the j th component which is measured by k th sensor, $j = 1,2,\ldots,N_c$, $k = 1,2,\ldots,M$.

Let S_i represent the measurement vector obtained from the i th sensor:

$$S_i = \lfloor s_{i1}, s_{i2}, \ldots, s_{im_i} \rfloor, \quad i = 1,2,\ldots,M$$

s_{ik} is a k th element of S_i, $k = 1,2,\ldots,m_i$, m_i is the number of elements provided by the i th sensor, $\sum m_i = M$. The problem is that of calculating the weight vector. We propose to use the Euclidean distance measure, which can be defined as:

$$d_{ij} = \begin{cases} \left[\sum_{k=1}^{m_i}(s_{ik} - e_{jk})^2\right]^{\frac{1}{2}} & i = 1 \\ \left[\sum_{k=1}^{m_i}(s_{ik} - e_{j(k+m_{i-1})})^2\right]^{\frac{1}{2}} & i > 1 \end{cases} \quad i = 1,2,\ldots,N_c \text{ , } j = 1,2,\ldots,M \tag{12}$$

d_{ij} is the distance between S_i and E_j The distances between each sensor measurements and all faults can be captured in a vector form :

$$D_j = \left[d_{j1}, d_{j2}, \ldots, d_{jM}\right] \tag{13}$$

Each D_j represents the distances between from one object mode and all sensor measurement. Defining w_{ij} as $w_{ij} = \dfrac{1}{d_{ij}}$ and expressing in a vector form after normalizing, we have:

$w_i = \left[w_{i1}, w_{i2}, \ldots, w_{iM}\right]$, $i = 1,2,\ldots,N_c$, where w_{ij} represents the similarity between component i and measurement j . The similarity values are normalized such that, for a given component i , the contributions of all measurements equal unity, i.e.,

$$\sum_{j=1}^{M} w_{ij} = 1, \quad i = 1,2,\ldots,N_c \text{ and } 0 \le w_{ij} \le 1$$

3 .4 D-S fusion

According to D-S rule formula (2), suppose m_1 , m_2 respectively corresponds to mass function assignment on the same frame of discernment Θ , mode recognized are respectively $A_1, A_2, \ldots, A_K$ and $B_1, B_2, \ldots, B_K$. In formula (3), k is the addition of all the mass functions multiply, which includes wholly contradictory hypotheses A_i and B_j , contradictory hypothesis means that the two object modes can't coexist at the same time, or they are repellent each other. Here ϕ stands for vacant sets. In formula (2), A refers to a comprehensive mode of combination object mode A_i and B_j , the mass function value $m(A)$ of mode A is the addition of all the mass function multiply that includes hypotheses A_i and B_j . In fault mode that needs to be tested, as for as specific engine fault diagnosis is concerned, it means the sets of each fault components that are seeked, $m(A)$ stands for the mass function value that are distributed to each component to be tested after D-S fusion.

4 NUMERICAL EXAMPLE

Table 1 shows the measured value using two sensors that need to be tested on engine components.

Table 1: measured Value using two sensors

Object mode	sensor	
	Temp	Vib
$C(e_1)$	0.1637	0.2380
$C(e_2)$	0.0904	0.0660
$C(e_3)$	0.1827	0.0016
$C(e_4)$	0.0563	0.2048
$C(e_5)$	0.0646	0.1504

We can calculate degree of belief $\beta_j(e_i)$ by formula (10). The number of sensor $M = 2$ and the number of fault components $N_C = 5$. According to specific experimental data, we select certain coefficient $\lambda_1 = \lambda_2 = 0.5$, adjustment coefficient $k = 0.2$. From formula (7), we can calculate that; $\alpha_1 = 0.1827$, $\alpha_2 = 0.2380$. Results are summarized in the table 2.

Table 2 degree of belief value of components to be tested

Object mode	**Sensor 1 (Temp)**	**Degree of belief ($\beta_1(e_i)\ i=1,2,\ldots,5$)**	**Object mode**	**Sensor 2 (Vib)**	**Degree of belief ($\beta_2(e_i)\ i=1,2,\ldots,5$)**
$C_1(e_1)$	0.1637	0.2195	$C_2(e_1)$	0.2380	0.2831
$C_1(e_2)$	0.0904	0.1212	$C_2(e_2)$	0.0660	0.0785
$C_1(e_3)$	0.1827	0.2450	$C_2(e_3)$	0.0016	0.0019
$C_1(e_4)$	0.0563	0.0755	$C_2(e_4)$	0.2048	0.2436
$C_1(e_5)$	0.0646	0.0866	$C_2(e_5)$	0.1504	0.1789

The weight vectors are determine for vibration Sensor $\vec{w}_1 = [0.05, 0.05, 0.39, 0.41, 0.1]$ and for temperature sensor $\vec{w}_2 = [0.04, 0.32, 0.18, 0.40, 0.06]$, table 3 shows calculated mass function $m_j(e_i)$ of fault diagnosis in each engine component and the unassigned probability masses based on the weight associated with the two sensors. We can also calculate fusion mass function and the unidentified values, as is shown in table 3.

$$\gamma_1 = \left(\frac{N_c \lambda_1}{\sum_{i=1}^{5} C_1(e_i)} - 1\right)/(N_c - 1) = 0.8706$$

$$\gamma_2 = \left(\frac{N_c \lambda_2}{\sum_{i=1}^{5} C_2(e_i)} - 1\right)/(N_c - 1) = 0.6958$$

$$R_1 = \frac{\lambda_1 \alpha_1 \gamma_1}{\sum_{j=1}^{2} \lambda_j \alpha_j \gamma_j} = 0.4898$$

$$R_2 = \frac{\lambda_2 \alpha_2 \gamma_2}{\sum_{j=1}^{2} \lambda_j \alpha_j \gamma_j} = 0.5101$$

$$\beta_1(e_1) = \frac{C_1(e_1)}{\sum_{i=1}^{5} C_1(e_i) + M \times k(1 - R_1)(1 - \lambda_1 \alpha_1 \gamma_1)} = 0.2195$$

We can also calculate other degree of belief values, as is shown in table 2.

Table 3 mass function value of components to be tested and multi-sensor fusion

Object mode	$\beta_1(e_i)$ $i=1,2,\ldots,5$	$\vec{w}_1$	$M_1(e_i)$ $i=1,2,\ldots,5$	**Object mode**	$\beta_2(e_i)$ $i=1,2,\ldots,5$	$\vec{w}_2$	$M_2(e_i)$ $i=1,2,\ldots,5$	**Fusion** $M_1(e_i)\oplus M_2(e_i)$ $i=1,2,\ldots,5$
$C_1(e_1)$	0.2195	0.05	0.0109	$C_2(e_1)$	0.2831	0.04	0.0113	0.01949
$C_1(e_2)$	0.1212	0.05	0.0060	$C_2(e_2)$	0.0785	0.18	0.0141	0.01755
$C_1(e_3)$	0.2450	0.39	0.0955	$C_2(e_3)$	0.0019	0.32	0.0006	0.08478
$C_1(e_4)$	0.0755	0.41	0.0309	$C_2(e_4)$	0.2436	0.40	0.0974	0.1144
$C_1(e_5)$	0.0866	0.1	0.00866	$C_2(e_5)$	0.1789	0.06	0.0107	0.01691
Diagnosis result								e_4 fault

For temperature: $M(\theta) = 0.8481$; For vibration: $M(\theta) = 0.8659$

In fault judgment principles based on D-S evidential theory, fault components should have maximal mass function value. We consider the conditions that affect the determination of fault and determine fault in specific component. Here it is 0.1144 for e_4 .

4 DISCUSSION ON FAULT DIAGNOSIS RESULTS

According to the formal fusion algorithm and fault judgment rules, we can get fusion results for engine component shown in the table 3. Each component mass function value and unidentified mass function value been tested by temperature and vibration are presented.

The mass function based on the weight associated with the two sensors. According to table 2, weighted mass functions are listed in table 3. In the experiment, we find that, in the five components been tested, the mass function value got by the two kinds of sensor separately is much similar to each other. If we only use one kind of sensor mass function assignment to recognize fault components, the situation that fault components cannot be identified will happen, and even worse that we may get wrong results.

When the fault components can't be found by use of two kinds of sensor separately, however, after fusion, we can precisely recognize fault component e_4 , it is identical to the real situation. That's to say, multi-sensor data fusion based on D-S evident theory enhanced the analyzability of the equipments, effectively raised the fault mode recognition ability, and raised fault components orientation precision rate.

5 CONCLUSION

This paper discusses the fault diagnostic problem for engine components. Within this framework we propose weight normalization and basic probability assignments for fusion mass function assignment. Each weight represents the similarity measure between a measurement and each engine component. From the experiment results we can see that, if the components tested is properly chosen, and the signal testing result is precise, then the fault diagnosis method based on multi-sensor data fusion can precisely find the fault components, moreover, you don't have to know the inner principle and structure of the engine components, and it's an effective blind diagnosis method. The numerical studies indicate that the proposed weighted and the diagnosis identification method can make better diagnosis decisions.

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