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Engine fault diagnosis based on sensor data fusion using evidence theory

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Abstract

Evidence theory is widely used in fault diagnosis due to its efficiency to model and fuse sensor data. However, one shortcoming of the existing evidential fault diagnosis methods is that only the basic probability assignments in singletons can be generated. In this article, a new evidential fault diagnosis method based on sensor data fusion is proposed. Feature matrix and diagnosis matrix are constructed by sensor data. A discrimination degree is defined to measure the difference between the sensor reports and feature vector. The basic probability assignment of each sensor report can be determined by the proposed discrimination degree. One merit of the proposed method is that not only singletons but also multiple hypotheses are considered. The final diagnosis result is obtained by the combination of several sensor reports. A practical fault diagnosis application is illustrated to show the efficiency of the proposed method.

Keywords

Fault diagnosis, sensors, data, uncertainty, probabilistic analysis

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Introduction

Fault diagnosis is widely used in real life. It is investigated and applied to many areas such as electrical motors,[1] analog circuits,[2] and dynamic systems.[3] Some particular tools are used to develop approaches to intelligent fault diagnosis. For example, a statistics analysis method is applied to fault diagnosis of rolling element bearings.[4] In addition, neural network,[5–7] support vector machine,[8] and other theories[9–13] are also applied to fault diagnosis.

Since the fault diagnosis and health management in real system are very complex with uncertain information, some efficient multi-criterion decision-making methods, such as analytic hierarchy process (AHP)[14–17] and technique for order of preference by similarity to ideal solution (TOPSIS),[18,19] are also applied to handle fault diagnosis.[20–22] In addition, decision-making, optimization, as well as fault pattern recognition are often inevitable to deal with uncertain information.[23–27] As a result, many math tools, such as fuzzy sets theory[28] rough sets theory,[29] and D numbers,[30] are adopted to handle the vague and uncertain information. The Dempster–Shafer evidence theory[31,32] (evidence theory) is efficient to quantify the imprecision and uncertainty in reliability and failure analysis. Due to its efficiency to represent and fuse uncertain information, evidence theory is widely used in many real systems,[33–38] such as credal classification,[34] reliability analysis,[39] uncertainty measure,[40] and failure modes' evaluation.[41] However, the application of evidence theory is sometimes limited for conflicting evidence. Some methods are proposed to handle the conflicting evidence.[42,43]

Recently, evidence theory is applied to fault diagnosis in some researches. A typical method is proposed by

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Basir and Yuan.[44] The multi-sensor engine diagnosis problem is framed in the context of evidence theory. However, the evidence theory is applied to fault diagnosis without the consideration of multiple hypotheses so that the advantage of evidence theory is not made most of. In addition, evidence theory is combined with other math tools to apply in a certain area in some articles. A new method[45] is introduced based on data-driven random fuzzy evidence acquisition and evidence theory and proved to have high accuracy and reliability with a good agreement with experimental data. Neural network and evidence theory[46] are combined in motor fault diagnosis model in order to reduce the uncertainty of the traditional method. A new weighted average method[47] based on the evidence theory and Deng entropy that can increase the accuracy of decision-making in fault diagnosis is proposed. A new combination rule[48] is built to allocate the conflicted information from multi-sensors based on the support degree of focal element in order to solve the uncertain information.

In this article, a method of engine fault diagnosis based on sensor data fusion is proposed. The feature matrix and diagnosis matrix are constructed for not only singletons but also multiple hypotheses. The mass functions are obtained by the comparison of two matrixes and combined by Dempster's combination rule. Decision is made according to the results. The main advantage of the proposed method is that the multiple hypotheses are taken into consideration so that uncertain information can be represented and fused efficiently.

The rest of the article is organized as follows. Section "Preliminaries" introduces the preliminaries. Section "An evidential fault diagnosis" presents the new method developed in this study. In section "Application and discussion," the validity and reliability of the proposed approach are tested in a real application. The study is briefly concluded in section "Conclusion."

Preliminaries

In this section, some preliminaries are briefly introduced.

Dempster–Shafer evidence theory

Dempster–Shafer evidence theory[31,32] (abbreviate as evidence theory) has many advantages to handle uncertain information. First, evidence theory allows probability masses to be assigned to not only singletons but also multiple hypotheses rather than only singleton subsets in comparison to the probability theory. Second, information from different sources can be combined without a prior distribution. Third, instead of forced to be assigned to some singleton subsets, a degree of ignorance can be allowed in some situations. A few basic concepts are introduced as follows.

Let Ω be a set of mutually exclusive and collectively exhaustive events, indicted by

$$\Omega = \{X_1, X_2, \ldots, X_i, \ldots, X_N\} \tag{1}$$

The set Ω is called a frame of discernment. The power set of Ω is indicated by 2^{Ω}, namely

$$\begin{aligned} 2^{\Omega} = \{\emptyset, \{X_1\}, \{X_2\} \ldots, \{X_N\}, \{X_1, X_2\}, \ldots, \\ \{X_1, \ldots, X_i\}, \ldots, \{X_1, \ldots, X_N\}\} \end{aligned} \tag{2}$$

If $A \in 2^{\Omega}$, A is called a proposition. In the power set 2^{Ω}, $\emptyset$ is called the empty set, the singletons are $\{X_1\}, \{X_2\}, \ldots, \{X_N\}$, and the multiple hypotheses are $\{X_1, X_2\}, \ldots, \{X_1, \ldots, X_i\}, \ldots, \{X_1, \ldots, X_N\}$.

For a frame of discernment Ω, a mass function is a mapping m from 2^{Ω} to $[0, 1]$, formally defined by

$$m : 2^{\Omega} \rightarrow [0, 1] \tag{3}$$

which satisfies the following condition

$$m(\emptyset) = 0 \quad \text{and} \quad \sum_{A \in 2^{\Omega}} m(A) = 1 \tag{4}$$

In evidence theory, a mass function is also called a basic probability assignment (BPA). BPA reflects the degree of evidence support for the proposition of A in recognition framework. If $m(A) \succ 0$, A is called a focal element, and the union is called the core of the mass function.

Assume there are two BPAs indicated by m_1 and m_2, Dempster's rule of combination is used to combine them as follows

$$m(A) = \begin{cases} \frac{1}{1-K} \sum\limits_{B \cap C = A} m_1(B) m_2(C), & A \neq \emptyset \\ 0, & A = \emptyset \end{cases} \tag{5}$$

where

$$K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C) \tag{6}$$

In evidence theory, K is a coefficient to measure the conflict between evidence. Note that Dempster's rule of combination is only applicable to such two BPAs which satisfy the condition $K \prec 1$. It should be noted that the conflict in evidence theory is an open issue.[49] Many methods have been proposed to address this issue.[42,43,50] Another issue is how to handle dependent evidence combination in real application, which also greatly affect data fusion result.[51,52]

An evidential fault diagnosis

A new method to represent the multiple hypotheses

Assuming N faults of an engine are taken into consideration, the frame of discernment is constructed as

$$X = \{X_0, X_1, X_2, \ldots, X_i, \ldots, X_N\} \tag{7}$$

where X_0 represents the absence of faults and $X_i(i = 1, 2, \ldots, N)$ represents the presence of the ith fault.

Then, the power set of X is constructed

$$\begin{aligned} 2^X = \{&\varnothing, \{X_0\}, \{X_1\}, \ldots, \{X_N\}, \{X_0, X_1\}, \ldots, \\ &\{X_0, \ldots, X_i\}, \ldots, \{X_0, \ldots, X_N\}\} \end{aligned} \tag{8}$$

Here, the multiple hypotheses represent that it is not sure which state in the multiple hypotheses occurs. For example, $\{X_0, X_1\}$ is regarded as an uncertain state that it is not sure whether the engine is in state X_0 or state X_1.

It can be seen that there are $2^{N+1} - 1$ states of the engine totally. In this article, the term N' is used to represent the amount of the states: $N' = 2^{N+1} - 1$. For the sake of convenience, the power set is presented as follows

$$2^X = \{\varnothing, H_1, \ldots, H_{N+1}, H_{N+2}, \ldots, H_{N'}\} \tag{9}$$

For example, when two possible faults of an engine are taken into consideration:

- X_0: free of any faults;
- X_1: exhaust valve fault;
- X_2: piston ring fault.

The frame of discernment is established as follows

$$X = \{X_0, X_1, X_2\} \tag{10}$$

Then, the power set of X is constructed as follows

$$\begin{aligned} 2^X = \{&\varnothing, \{X_0\}, \{X_1\}, \{X_2\}, \{X_0, X_1\}, \\ &\{X_0, X_2\}, \{X_1, X_2\}, \{X_0, X_1, X_2\}\} \end{aligned} \tag{11}$$

Here, $N = 2$, and $N' = 2^{N+1} - 1 = 7$. According to equations (8) and (9), H_1 represents $\{X_0\}$, H_2 represents $\{X_1\}$, and H_7 represents $\{X_0, X_1, X_2\}$.

From a sensor attached to the engine, one or more characteristic values that describe some features of the engine can be obtained. Assuming M features and characteristic values are obtained for X_i, $\lambda_j(j = 1, 2, \ldots, M)$ are used to represent the features. Several feature vectors are constructed to represent its state

$$X_i = [x_{i1}, x_{i2}, \ldots, x_{iM}] \tag{12}$$

where x_{ij} represents the jth characteristic value obtained from the sensors when X_i happens.

With regard to $\{X_0\}, \ldots, \{X_N\}$, $N + 1$ feature vectors are constructed, which are also the feature vectors of the singleton subsets in equation (9). Because the multiple hypotheses represent that the condition of the engine is uncertain according to the given data, the characteristic values of the multiple hypotheses are obtained by the average characteristic value of its elements. For example, the feature vector of H_{N+2} is obtained as follows

$$\begin{aligned} H_{N+2} &= \{X_0, X_1\} \\ &= \left[h_{(N+2)1}, h_{(N+2)2}, \ldots, h_{(N+2)M}\right] \end{aligned}$$

where

$$h_{(N+2)j} = \frac{x_{0j} + x_{1j}}{2}, \quad j = 1, 2, \ldots, M \tag{13}$$

Based on the vectors, a feature matrix can be constructed

$$H = \begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ H_{N'} \end{bmatrix} \tag{14}$$

$$H = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1M} \\ h_{21} & h_{22} & \cdots & h_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N'1} & h_{N'2} & \cdots & h_{N'M} \end{bmatrix} \tag{15}$$

$H_k(k = 1, 2, \ldots, N')$ is the feature vectors of the $2^{N+1} - 1$ states of the engine.

For an engine to be diagnosed, several groups of characteristic values can be obtained by the data from the sensors. Here, each group of characteristic values is represented by a diagnosis vector. Assuming L diagnosis vectors is measured, a diagnosis matrix is constructed to represent the engine's real state

$$R = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_L \end{bmatrix} \tag{16}$$

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1M} \\ r_{21} & r_{22} & \cdots & r_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ r_{L1} & r_{L2} & \cdots & r_{LM} \end{bmatrix} \tag{17}$$

Each row of the diagnosis matrix functions as a piece of evidence in the fault diagnosis.

Construction of mass functions

How to determine the BPAs is still an open issue.[53] In this article, the smaller the discrimination between H_k and $R_l (l = 1, 2, \ldots, L)$, the more probable the H_k state of the engine. Thus, the discrimination of them is used to construct the mass functions.

First, the discrimination degree between the feature vectors and diagnosis vectors is calculated. Take a diagnosis vector R_l for example. The discrimination degree between $R_l = [r_{l1}, r_{l2}, \ldots, r_{lM}]$ and $H_k = [h_{k1}, h_{k2}, \ldots, h_{kM}]$ is calculated by the Euclidean distance

$$d_{lk}^2 = \sum_{j=1}^{M} (r_{lj} - h_{kj})^2 \tag{18}$$

Once the discriminations between $H_k (k = 1, 2, \ldots, N')$ and $R_l (l = 1, 2, \ldots, L)$ are calculated, a discrimination matrix can be established[54]

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1N'} \\ d_{21} & d_{22} & \cdots & d_{2N'} \\ \vdots & \vdots & \ddots & \vdots \\ d_{L1} & d_{L2} & \cdots & d_{LN'} \end{bmatrix} \tag{19}$$

The kth column of equation (19) represents the discrimination degree between H_k and L diagnosis vectors. The less the values, the more similarity between the engine's state and the H_k state.

The similarity measure between R_l and H_k is defined as follows

$$s_{lk} = \frac{1}{d_{lk}} \tag{20}$$

Then, the similarity matrix is established

$$S = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1N'} \\ s_{21} & s_{22} & \cdots & s_{2N'} \\ \vdots & \vdots & \ddots & \vdots \\ s_{L1} & s_{L2} & \cdots & s_{LN'} \end{bmatrix} \tag{21}$$

The mass functions are obtained by normalizing the similarity matrix s, shown as follows

$$M = \begin{matrix} \\ m_1 \\ m_2 \\ \vdots \\ m_L \end{matrix} \begin{matrix} \begin{matrix} H_1 & H_2 & \cdots & H_{N'} \end{matrix} \\ \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1N'} \\ p_{21} & p_{22} & \cdots & p_{2N'} \\ \vdots & \vdots & \ddots & \vdots \\ p_{L1} & p_{L2} & \cdots & p_{LN'} \end{bmatrix} \end{matrix} \tag{22}$$

p_{lk} means the probability of the occurrence of the kth state in the lth mass function.

Combination and decision

According to equation (22), L mass functions $m_l (l = 1, 2, \ldots, L)$ are obtained. Here, they are combined by equations (5) and (6). A mass function can be obtained as follows

$$m(H_1) = p_1, m(H_2) = p_2 \ldots, m(H_{N'}) = p_{N'} \tag{23}$$

According to equations (8) and (9), H_1 represents $\{X_0\}$, and $H_{N'}$ represents X. Equation (23) represents the mass function of the state of the engine

$$m(\{X_0\}) = p_1, m(\{X_1\}) = p_2, \ldots, m(X) = p_{N'} \tag{24}$$

Decision is made on the base of this mass function. The engine is free of any faults if $m(\{X_0\})$ is greater than the others obviously. The fault X_1 occurs if $m(\{X_1\})$ has the largest value. When the diagnosis state is a singleton, its implication is distinct and explicit. When the diagnosis state is a multiple hypothesis, it indicates an uncertain condition. For example, if $m(\{X_0, X_1\})$ has the largest BPA, it indicates that we are not sure whether the engine is free of faults or the fault X_1 has occurred. It may indicate that the fault X_1 is going to occur as well. Because of a lack of information, the decision-maker cannot obtain the final decision and more information about the engine is needed.

The decision-making process is detailed as follows: after obtaining the final result combined by L original mass functions according to data from the sensors, the state of the engine is determined if one BPA is obviously greater than the others. Here, it is suggested that the state of the engine can be obtained if

$$m\{H_a\} - m\{H_n\} \succ 0.1 (n = 1, 2, \ldots, N', n \neq a) \tag{25}$$

If H_a is a singleton, the state of the engine is definite. If H_a is a multiple hypothesis, it is the condition that we are not sure which state in the multiple hypothesis occurs. The decision-maker should add more information to obtain a result with a higher reliability.

A simple example will illustrate the decision rule. Assume a frame of discernment $X = \{X_0, X_1\}$ where X_0 represents the engine is free of any faults and X_1 means some failure happens. The power set of X is constructed as follows

$$2^X = \{\emptyset, \{X_0\}, \{X_1\}, \{X_0, X_1\}\}$$

Here, $N = 1$ and $N' = 3$. For convenience, the power set can be represented as

$$2^X = \{\emptyset, H_1, H_2, H_3\}$$

If the basic probability functions are obtained as follows

$$m(H_1) = 0.64$$
$$m(H_2) = 0.12$$
$$m(H_3) = 0.24$$

It can be easily seen that

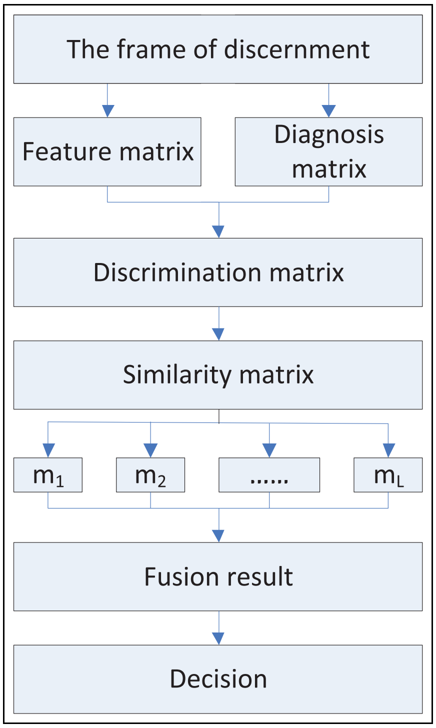

Figure 1. The flowchart of the proposed method.

$$m(H_1) - m(H_2) \succ 0.1$$
$$m(H_1) - m(H_3) \succ 0.1$$

which satisfy equation (25) when $a = 1$. Thus, decision can be made that $H_1(\{X_0\})$ happens. That is to say, the engine is free of any faults.

The algorithm of the proposed method

In summary, the algorithm of the proposed method is shown in Figure 1 and detailed as follows:

- *Step 1*. Construct the frame of discernment and the power set.
- *Step 2*. Construct the feature matrix based on the reality and experience.
- *Step 3*. Collect the characteristic value and establish the diagnosis matrix by data from sensors.
- *Step 4*. Compare the feature matrix and the diagnosis matrix to get the discrimination matrix, similarity matrix, and mass functions eventually.
- *Step 5*. Combine the mass functions by evidence theory.
- *Step 6*. Make decision based on the final result.

Application and discussion

A practical application of the proposed method

In this section, an application is given to show the proposed fault diagnosis method. In this case, two possible faults of an engine are taken into consideration:

- X_0: free of any faults;
- X_1: exhaust valve fault;
- X_2: piston ring fault.

The fault diagnosis of an engine is as follows:

Step 1. First, as follows, a frame of discernment is established

$$X = \{X_0, X_1, X_2\} \tag{26}$$

Then, the power set of X is constructed as follows

$$2^X = \{\varnothing, \{X_0\}, \{X_1\}, \{X_2\}, \{X_0, X_1\}, \{X_0, X_2\}, \{X_1, X_2\}, \{X_0, X_1, X_2\}\} \tag{27}$$

Step 2. A feature matrix is constructed based on the previous knowledge and experience with regard to the characteristic values. In this experiment, two acceleration sensors and one acoustic sensor are used to obtain the original data. One acceleration sensor is mounted on the cylinder cover near the outlet valve. Another is mounted on the cylinder cover near the inlet valve. Their peak-to-peak value (P-to-P) in the time domain and the frequency of the maximum spectrum (F_{max}) are calculated as four features. For convenience, they are represented as $\lambda_1, \lambda_2, \lambda_3$, and λ_4. With regard to the acoustic signal, its mean pressure level (MPL) and the centrobaric frequency of the spectrum (F_c) are calculated as another two features, represented as λ_5 and λ_6. Six features are taken into consideration for each condition of the engine and their characteristic values for each state are obtained.[44] Taking no account of the empty set, seven feature vectors are constructed based on the data

$$H = \begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ H_7 \end{bmatrix} \tag{28}$$

$$H = \begin{matrix} \{X_0\} \\ \{X_1\} \\ \vdots \\ X \end{matrix} \overset{\begin{matrix} \lambda_1 & \lambda_2 & \cdots & \lambda_6 \end{matrix}}{\begin{bmatrix} h_{11} & h_{12} & \cdots & h_{16} \\ h_{21} & h_{22} & \cdots & h_{26} \\ \vdots & \vdots & \ddots & \vdots \\ h_{71} & h_{72} & \cdots & h_{76} \end{bmatrix}} \tag{29}$$

For convenience, the values of the singletons are shown in Table 1. According to equation (13), the values of the generated multiple hypotheses are obtained and shown in Table 2.

Step 3. Then, the characteristic values of the features are collected and a feature matrix is constructed by data from sensors as follows

Table 1. Features according to previous knowledge.

	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
$\{X_0\}$	313.5	559.6	378.6	557.4	152.9	762.7
$\{X_1\}$	1850.7	550.8	1734.5	597.2	152.3	808.2
$\{X_2\}$	2669.3	546.6	2567.4	534.8	152.7	724.1

Table 2. Features of the multiple hypotheses.

	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
$\{X_0, X_1\}$	1082.1	555.2	1056.6	577.3	152.6	785.5
$\{X_0, X_2\}$	1491.4	553.1	1473.0	546.1	152.8	743.4
$\{X_1, X_2\}$	2260.0	548.7	2151.0	566.0	152.5	766.2
$\{X_0, X_1, X_2\}$	1611.2	552.3	1560.2	563.1	152.6	765.0

Table 3. Features according to diagnosis vectors.

	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
R_1	1830.6	553.9	1780.5	600.2	152.5	780.3
R_2	1883.5	549.9	1702.4	590.0	151.9	813.6
R_3	1854.0	551.7	1738.1	595.4	152.1	797.5
R_4	1882.2	555.2	1757.3	575.5	152.5	802.4

$$R = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_4 \end{bmatrix} \tag{30}$$

$$R = \begin{matrix} \lambda_1 & \lambda_2 & \cdots & \lambda_6 \end{matrix} \\ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{16} \\ r_{21} & r_{22} & \cdots & r_{26} \\ \vdots & \vdots & \ddots & \vdots \\ r_{41} & r_{42} & \cdots & r_{46} \end{bmatrix} \tag{31}$$

It can be seen that four diagnosis vectors are obtained and shown in Table 3.

Step 4. In this step, equations (18)–(22) are utilized to construct the discrimination matrix, similarity matrix, and mass function matrix. The discrimination matrix is constructed by equation (18) and the data in Tables 1 and 3

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{17} \\ d_{21} & d_{22} & \cdots & d_{27} \\ d_{31} & d_{31} & \cdots & d_{37} \\ d_{41} & d_{42} & \cdots & d_{47} \end{bmatrix} \tag{32}$$

The results are illustrated in Table 4.

By equation (20), the similarity matrix is constructed. The mass functions are obtained by normalizing the similarity matrix. The results are shown in matrix M and Table 5

$$M = \begin{matrix} m_1 \\ m_2 \\ m_3 \\ m_4 \end{matrix} \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{17} \\ p_{21} & p_{22} & \cdots & p_{27} \\ p_{31} & p_{32} & \cdots & p_{37} \\ p_{41} & p_{42} & \cdots & p_{47} \end{bmatrix} \tag{33}$$

Step 5. Four mass functions m_1, m_2, m_3, and m_4 have been obtained. They are fused by equations (5) and (6). The final result is shown as follows

$$\begin{aligned} m\{X_0\} &= 0.000072 \\ m\{X_1\} &= 0.999644 \\ m\{X_2\} &= 0.000184 \\ m\{X_0, X_1\} &= 0.000013 \\ m\{X_0, X_2\} &= 0.000048 \\ m\{X_1, X_2\} &= 0.000032 \\ m\{X_0, X_1, X_2\} &= 0.000007 \end{aligned}$$

Step 6. It can be easily seen that the BPA of X_1 is obviously larger than the others. It can be confirmed that the fault X_1 (exhaust valve fault) exists.

Table 4. Results of the discrimination matrix.

l	d_{l1}	d_{l2}	d_{l3}	d_{l4}	d_{l5}	d_{l6}	d_{l7}
1	2066.2	57.6	1153.3	1041.6	462.5	568.4	313.5
2	2054.5	46.8	1173.4	1029.7	461.8	588.1	312.2
3	2055.3	11.9	1166.8	1029.9	455.1	580.7	304.5
4	2088.9	45.1	1133.0	1063.7	487.8	547.0	337.4

Table 5. Basic probability assignments of the states of the engine.

	$\{X_0\}$	$\{X_1\}$	$\{X_2\}$	$\{X_0, X_1\}$	$\{X_0, X_2\}$	$\{X_1, X_2\}$	$\{X_0, X_1, X_2\}$
m_1	0.0181	0.6482	0.0324	0.0358	0.0807	0.0657	0.1191
m_2	0.0158	0.6950	0.0277	0.0316	0.0704	0.0553	0.1042
m_3	0.0052	0.8980	0.0092	0.0104	0.0235	0.0185	0.0352
m_4	0.0153	0.7079	0.0282	0.0300	0.0655	0.0584	0.0947

Table 6. Performance accuracy when one piece of evidence is used.

Random error rate (%)	5	10	15	20	25
Performance accuracy (%)	99.99	51.45	16.45	0	0

Table 7. Performance accuracy when two pieces of evidence are used.

Random error rate (%)	5	10	15	20	25
Performance accuracy (%)	100	100	88.57	56.70	33.64

Compare the combination of four groups of mass functions and the combination of the former two, which is shown as follows

$$\begin{aligned} m\{X_0\} &= 0.013281 \\ m\{X_1\} &= 0.886276 \\ m\{X_2\} &= 0.029167 \\ m\{X_0, X_1\} &= 0.010151 \\ m\{X_0, X_2\} &= 0.026453 \\ m\{X_1, X_2\} &= 0.020075 \\ m\{X_0, X_1, X_2\} &= 0.014597 \end{aligned}$$

The more the diagnosis vectors, the more reliability of the combination result.

In some cases, the largest result may be a multiple hypothesis. For example, the BPA of $\{X_1, X_2\}$ is obviously larger than the others. In the previous example, that means we cannot make a final decision between the faults X_1 and X_2 (exhaust valve fault and piston ring fault), and more information is needed to make a final decision.

Reliability analysis

In this section, the reliability of the proposed methods is analyzed by a program which simulates the random error in actual measurement. Suppose a fault of the engine exists and we are asked to diagnose the engine by data obtained from the sensors with regard to the features. Equation (25) is regarded as the decision criteria in this analysis.

Here, piston ring fault (X_2) is taken as the fault which exists in the engine. A group of diagnosis vectors are generated with a random error rate no more than a certain percent (5%, 10%, etc.) to simulate the condition in actual application. First, only one evidence is used to diagnose the engine each time. The performance accuracy is shown in Table 6. It can be seen that the accuracy decreased quickly with the increased error rate.

When combining more evidence and the proposed method is applied, its performance is improved as a result of the fusion method. The performance accuracy when two and three pieces of evidence are used is shown in Tables 7 and 8, respectively. It indicates that using more evidence can reduce the influence of the random error in actual measurement and increase the reliability of the proposed method.

Comparison with the typical method

In this section, a comparison is made between the typical method and the proposed method in this article.

Basir and Yuan[44] had used three sensors (S_1, S_2, and S_3) to test the efficiency of the typical method. The

Table 8. Performance accuracy when three pieces of evidence are used.

Random error rate (%)	5	10	15	20	25
Performance accuracy (%)	100	100	100	100	98.59

Table 9. Performance accuracy of the typical method when different numbers of sensors are used.

Used sensor(s)	S_1	S_2	$S_1 + S_2$	$S_1 + S_2 + S_3$
Performance accuracy (%)	80	82	89	94

performance accuracy when different numbers of sensors are used is shown in Table 9. Through Tables 6–9, it can be seen that both two methods perform well in the application and the proposed method performs a little better than the typical one when more than two pieces of evidence are used.

From the angle of the model construction, in the typical method, the mass functions of multiple hypotheses are set to 0, which reduces the calculation amount but limits this method to cases where it is clear that no more than one fault happens to the engine. However, considering the multiple hypotheses, the proposed method not only keeps the virtue of the typical method but also provides more uncertain information to the decision-maker to recognize cases where two or more faults happen at the same time.

Conclusion

In this article, a new method of engine fault diagnosis based on sensor data fusion is presented. First, the construction of the frame of discernment is determined. Then, feature matrix and diagnosis matrix are constructed with regard to focal elements in the power set. The advantage of the proposed method is that the multiple hypotheses are taken into consideration. Several mass functions of the sensor reports are obtained by the discrimination degree between the feature matrix and diagnosis matrix. Then, the final diagnosis result is obtained by the combination of several sensor reports. Decision is made based on the final fusion result. The effectiveness of the algorithm is demonstrated by a practical fault diagnosis application.

Declaration of conflicting interests

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