Diagnosing Valve Clearance Fault using Multi-Parameter Fusion

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Abstract - *In this paper, the Dempster-Shafer evidential reasoning is used in a new domain - Fault Diagnosis of Reciprocating Machinery. Other than the new application for the Demspter-Shafer approach, this paper describes a new way of implementation - multi-parameter fusion - which requires selected parameters extracted from every sensor to be fused. This is in contrast with existing methods that need the eigenvectors to be fused. By selecting the relevant parameters as compared to generating the eigenvectors, this method is much easier to implement. Through the implementation, it is shown that this method decreases the uncertainty in the diagnosis systems. In addition, after the preprocessing of the information extracted from each sensor, it can reduce the computing time at the fusion stage.*

Keywords: Dempster-Shafer evidential reasoning, fault diagnosis, multi-parameter fusion

1 Introduction

Sensor systems have been improving rapidly and ancillary data are increasingly available. As a result, interest in extracting the higher level information contained in all kinds of sensing contexts has led to extensive demand for computer-based, automated methods for the analysis of multi-source data. This requirement gives rise to many information integration and fusion methods. The potential advantages in integrating and fusing information from multiple sensors are that the information can be obtained more accurately and in less time and at a less cost. Features that are impossible to perceive with individual sensor can now be obtained through the use of multiple sensors. Multiple sensors, together with information integration and fusion, have been used in many areas, such as navigation, target identification, robot control and multi-target tracking.

In this paper, the application of information integration and fusion has been broadened to fault diagnosis in machinery. Up to now, the conventional method used to diagnose fault in machinery is to observe the change of FFT (Fast Fourier Transformation) spectrum of a single sensor. For large rotational machinery, because its signal from displacement sensor is very simple, like pure sine curve, the information presented in the spectrum is enough to be used for diagnosis. However for reciprocating machinery, such as reciprocating compressor and diesel engine, due to the complex structure and multi-excite sources existing in diesel engine, the vibration signals collected from the engine surface have the following characteristics:

- Presence of a number of self-exciting vibration and forced vibration in the diesel engine that is running. Therefore the width of spectrum in frequency domain is very large.
- The vibration signals in the time domain are more complex compared to a large-scale rotational machinery, which is a pure sine curve.
- In a diesel engine, such as 4135 engine, the stroke cycles are fixed. Therefore the time series appear periodical. However in every period, there exist many other periodical vibrations within the stroke cycle.

So using single sensor's information is not enough to diagnose fault types. In this paper, several acceleration sensors are used to sample the vibration signals from the surface of a 4135 diesel engine. A new fusion method, multi-parameter fusion, is used to get the final judgment.

The remainder of this paper is organized as follows. In the second section, the fundamental knowledge of evidence reasoning is introduced. The parameters used for information fusion are studied in the third section of this paper. In the fourth section, the above selected parameters are fused and the final judgment is given. In the same section, some questions related to fusion are discussed. And the conclusion is given at the end of this paper.

2 Preliminary of Evidence Reasoning

There are many algorithms, which can be used to integrate multiple sensors' information. Among them, distributed Kalman filtering and the Bayesian approach are well known. Bayesian approach offers a highly formalized and rigorous way to assign and propagate confidence. However, these algorithms require substantial a prior information, such as initial values and initial covariance matrices for distributed Kalman filtering and prior probabilities for the Bayesian approach. In many cases, prior information is either unavailable or not known precisely. Another weakness is that they cannot represent uncertainty in the systems very well. These inadequacies give rise to the Evidence Reasoning.

Evidence Reasoning, also called the 'Dempster-Shafer theory' or the 'belief function theory', has been found useful in dealing with uncertainty in many domains, for instance, diagnostic system and radar surveillance system.

The basic notions of Evidence Reasoning were presented by G. Shafer (1976). The following concepts are the fundamental concepts of D-S theory: frame of discernment, basic probability assignment (BPA), and belief function and plausibility function. They are introduced as follows.

A frame of discernment *Q* is a finite nonempty set.

The basic probability assignment (BPA) on *Q* is a function

$$m: P(Q) \text{ ® } R_+ \quad (1)$$

where *P(Q)* is the powerset of *Q* and R_+ is the set of nonnegative reals, satisfying the following conditions:

1. *m(Æ) = 0* (2)

2. $\sum_{\Delta \subseteq \Theta} m(\Delta) = 1$ (3)

For a given basic probability assignment *m* two functions are defined.

• A function *Bel*: *P(Q)* ® R_+ is called the belief function over *Q* (generated by m) iff for any *q Í Q*,

$$Bel(q) = \sum_{\Delta \subseteq q} m(\Delta) \quad (4)$$

• A function *Pl*: *P(Q)* ® R_+ is called the plausibility function over *Q* (generated by m) iff for any *q Í Q*,

$$Pl(q) = \sum_{\Delta \cap q \neq \varnothing} m(\Delta) \quad (5)$$

The plausibility function *Pl* can be definable by the belief function *Bel*:

$$Pl(q) = 1 - Bel(\Theta - q),\ for\ q \subseteq \Theta \quad (6)$$

From a given belief function, a basic probability assignment can be reconstructed:

$$m(q) = \sum_{\Delta \subseteq q} (-1)^{|q-\Delta|} Bel(\Delta),\ for\ q \subseteq \Theta \quad (7)$$

The union of all subsets *q Í Q* that are *focals* is called the *core* of *Q*.

A belief function *Bel* is called *Bayesian belief function* iff $Bel(q) + Bel(\Theta - q) = 1\ for\ q \subseteq \Theta$. The following conditions are equivalent.

1. *Bel* is *Bayesian*.
2. $Bel(q \cup \Delta) = Bel(q) + Bel(\Delta)$; $for\ q, \Delta \subseteq \Theta\ and\ q \cap \Theta = \varnothing$; (8)
3. *Bel=Pl*;
4. All focal elements are singletons.

Dempster's Rule of Evidence Combination:

Evidence obtained on the same subject from two probabilistically independent sources can be combined into joint evidence of the subject. For instance, two pieces of evidence expressed by two basic-probability-assignments $m_1(A)$ and $m_2(B)$ can be combined into a signal piece of joint evidence by

$$m_{12} = \begin{cases} \dfrac{\sum_{C=A\cap B} m_1(A)\cdot m_2(B)}{1-K}, & if\ \ C \neq \varnothing \\ 0, & if\ \ C = \varnothing \end{cases} \quad (9)$$

where the constant *K* is

$$K = \sum_{A\cap B=\varnothing} m_1(A)\cdot m_2(B) \quad (10)$$

which represents conflicting information in these two pieces of evidence. In (9), combined information is normalized after the conflicting information is removed. Dempster's rule reduces to Bayesian approach when the belief function is the same as the plausibility function.

3 Establishing Parameter Field

In this paper, a new fusion method is proposed – multi-parameter fusion. Multi-parameter fusion because the parameters, which represent the information contained in sampled signals, are extracted and these parameters are used in the fusion framework, instead of the eigenvectors.

The case study used in the research is a 4135 diesel engine. The parameters are:

Rated Engine Power: 80 horsepower

Rated Engine Speed: 1500rpm

Four states are simulated on this diesel engine. They are

- Normal
- Intake valve clearance is too small
- Intake valve clearance is too large
- Exhaust valve clearance is too large

Among these four states, three fault types were simulated in the intake valve and exhaust valve on the second cylinder head. Three points are selected to collect vibration signals. They are the first cylinder head, the second cylinder head and another one, which is in the middle point of piston stroke, on the surface of cylinder block.

Six parameters are extracted from the vibration signal of each sampling point. These six parameters can be divided into two categories, frequency domain and time domain. They are introduced as follows:

(1) Frequency domain parameters:

a. *IF* - Waveform Complexity in frequency domain

$$IF = -\sum_{i=1}^{N/2} X(i)\log X(i) \qquad (10)$$

where *X(i)* - the FFT spectrum

From the equation (10), it can be seen that *IF* is a frequency domain entropy, reflecting the complexity of FFT spectrum.

b. *CG* - the center frequency of spectrum

$$CG(X) = \sum_{K=1}^{N/2} \frac{K}{N/2} m(X(K)) \qquad (11)$$

where $m(X(K)) = X(K) \Big/ \sum_{j=1}^{N/2} X(j)$

X(K) - the FFT spectrum

k=1,2,¼,N

(2) Time domain parameters:

a. *IT* - Waveform Complexity in time domain

$$IT = -\sum_{i=1}^{m} \lambda_i \log \lambda_i \qquad (12)$$

where λ_i - the singular value of a time series according to its period

m - the numbers of periods in a time series

The physical significance of *IT* is to reflect the complexity of time series. It is time domain entropy.

b. σ - Nonperiod complexity

$$\sigma = \frac{m}{m-1} \sum_{i=2}^{m} \lambda^2{}_i \Big/ \sum_{i=1}^{m} \lambda^2{}_i \qquad (13)$$

where λ_i - the singular value of a time series according to its period.

c. D_x - the variance of time series

$$D_x = \frac{1}{n} \sum_{i=1}^{n} \left[x(t_i) - \bar{x}\right]^2 \qquad (14)$$

where n - the length of a time series

$\bar{x}$ - the mean value of whole series

$x(t_i)$ - the time series

d. α_4 - the kurtosis of time series

$$\alpha_4 = \frac{1}{n} \sum_{i=1}^{n} \left[x(t_i)\right]^4 \qquad (15)$$

The above six parameters reflect the information contained in vibration signals both from the frequency domain and time domain. For *IT* and σ, they reflect the time series' periodical characteristic because the single fault type shows the periodicity in time domain and the energy will increase in a certain frequency in spectrum, which is reflected by parameters, *IF* and *CG*. Variance D_x and Kurtosis α_4 are the measures of the data distribution.

4 Using Multi-parameter Fusion to Diagnose Valve Fault of a 4135 Diesel Engine

In this section, the above extracted parameters are fused using D-S theory. For simplification, the belief function is only calculated as the final results.

4.1 Defining the Basic Probability Assignment – Mass Function

There are many fusion methods to be used in different domain. In this paper, in light of the characteristics of vibration signal collected from the surface of 4135 diesel engine, the basic probability assignment (mass function) is defined as follows.

$$m_i\left(A_j\right)=\frac{w_i C_i\left(A_j\right)}{\sum_j w_i C_i\left(A_j\right)+N_s\left(1-R_i\right)\left(1-\boldsymbol{a}_i \boldsymbol{b}_i\right)} \quad (16)$$

$$m_i(\boldsymbol{q})=\frac{N_s\left(1-R_i\right)\left(1-\boldsymbol{a}_i \boldsymbol{b}_i\right)}{\sum_j w_i C_i\left(A_j\right)+N_s\left(1-R_i\right)\left(1-\boldsymbol{a}_i \boldsymbol{b}_i\right)} \quad (17)$$

$i=1, 2, \ldots, N_s, j=1, 2, \ldots, N_c$

where $C_i\left(A_j\right)=1 / d_{i,j}(X_i, Y_j)$ – Correlation Coefficient of sensor i for fault class j (18)

$d_{i,j}\left(X_i, Y_j\right)=\sum_{k=1}^{n}\left|x_{ik}-y_{jk}\right|$ –Manhattan Distance (19)

$\boldsymbol{a}_i=\max_j\left\{C_i(A_j)\right\}=1 / \min_j\left\{d_{i,j}(X_i, Y_j)\right\}$ – Maximum Correlation coefficient for sensor i (20)

$\boldsymbol{b}_i=\left(\frac{N_c \boldsymbol{a}_i}{\sum_j C_i\left(A_j\right)}-1\right) / \left(N_c-1\right)$ – Spread of correlation coefficient for sensor i, which includes the global factors affecting the diagnosis results. (21)

$R_i=\frac{\boldsymbol{a}_i \boldsymbol{b}_j}{\sum_k \boldsymbol{a}_k \boldsymbol{b}_k}$ – Reliability coefficient of sensor i (22)

N_c – Number of fault classes, $N_c=4$ here.

f_0 – normal
f_1 – small intake valve clearance
f_2 – large intake valve clearance
f_3 – large exhaust valve clearance.

N_s – Number of sensors, $N_s=3$ here.

w_i – weight coefficient, which is determined according to practical experience.

4.2 Applying the Multi-parameter Fusion

In this fusion framework as shown in Figure 1, some assumptions are proposed to process the multi-sensor and multi-parameter fusion. First, different sensors are independent from others. Second, different fault types are independent from others. That is to say, no two fault types can coexist in the engine simultaneously. Table 1 presents the fusion results.

There are 19 cases tested in this paper. Out of the 19 final results, only two cases are wrongly categorized. The verification degree – ratio of correct diagnosis over the total number of cases – is 17/19. This shows that the method is effective in its diagnosis. For illustration, only four cases are listed in the Table 1.

From the results listed in Table 1, it can be seen that using single sensor, some types of fault cannot be determined. These are denoted as 'Uncertain'. After fusing the parameters extracted from every sensor, the verification degree increased while the uncertainty decreases.

In order to reduce computing time, the user can select simple parameters. This is unlike the use of eigenvectors which are fixed as the eignevectors correspond to their respective fault types. In so doing, this multi-parameter fusion method overcomes the shortcomings of the D-S fusion algorithm by simplification and thereby reducing the complexity of the problem.

5 Conclusions

In this paper, a new fusion method – multi-parameter fusion, has proposed and implemented to diagnose the fault types of diesel engine. Through the analysis of fusion results, the following conclusions can be drawn:

- Multi-parameter fusion is a feasible method to be used in fault diagnosis.
- This method has many advantages, such as decreasing uncertainty in the fusion and presents high verification probability as compared to the single sensor. It can reduce

the computing complexity when compared with using eigenvector fusion.

- A new diagnosis method using D-S theory has been presented.

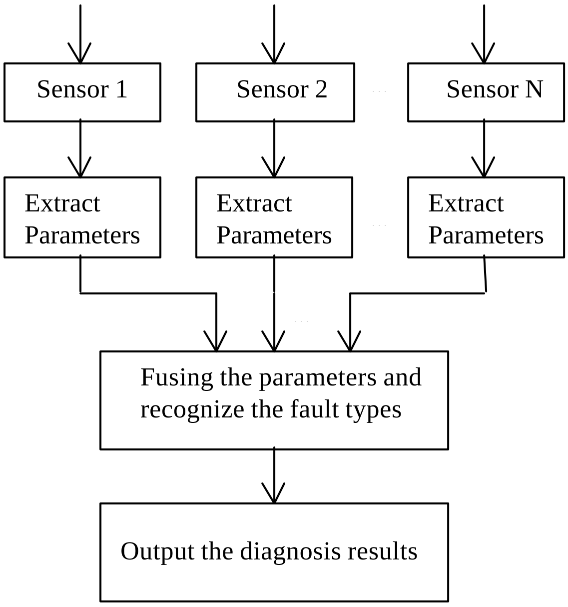

Figure 1. The flow chart of diagnosing system using D-S Evidential Theory

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Table 1. The multi-sensor and multi-parameter fusion result

Fault types	Sensor	Mass function **m(f$_i$)**/belief function **Bel(f$_i$)** **m(q)**	**m(f$_0$)**	**m(f$_1$)**	**m(f$_2$)**	**m(f$_3$)**	Fusion result
f$_0$ (Normal)	Sensor1	0.4962	0.3704	0.0073	0.0146	0.1115	Uncertain
	Sensor2	0.4433	0.4857	0.0695	0.0007	0.0009	Uncertain
	Sensor3	0.3825	0.6036	0.0043	0.0035	0.0061	f_0
	Fusion	0.2097	0.7225	0.0261	0.0058	0.0360	**f_0**
f$_1$ (Intake Valve Clearance is too small)	Sensor1	0.3566	0.0046	0.5921	0.0420	0.0047	f_1
	Sensor2	0.5167	0.1980	0.2126	0.0320	0.0407	Uncertain
	Sensor3	0.4400	0.0032	0.4377	0.0030	0.1162	Uncertain
	Fusion	0.2234	0.0654	0.6272	0.0274	0.0565	**f_1**
f$_2$ (Intake Valve Clearance is too Large)	Sensor1	0.5178	0.0262	0.1925	0.2394	0.0242	Uncertain
	Sensor2	0.4821	0.0030	0.0039	0.3562	0.1548	Uncertain
	Sensor3	0.3048	0.0015	0.0010	0.6867	0.0024	f_2
	Fusion	0.2181	0.0097	0.0615	0.6506	0.0601	**f_2**
f$_3$ (Exhaust Valve Clearance is too Large)	Sensor1	0.4132	0.0532	0.0053	0.0115	0.5168	f_3
	Sensor2	0.5172	0.0122	0.0149	0.2771	0.1785	Uncertain
	Sensor3	0.4155	0.0062	0.0408	0.0251	0.5125	f_3
	Fusion	0.2352	0.0261	0.0220	0.1074	0.6093	**f_3**