A Permutation Entropy-based Importance Measure for Condition Monitoring Data Fusion in Fault Diagnosis

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***Abstract*—In condition monitoring and fault diagnosis, how to measure the importance degree of different condition monitoring (CM) data before data fusion is a vital issue. We propose an importance measure that can be modeled using a weighted average function. The weight is measured with the relative scale of the permutation entropy from each fault feature variable. Compared with some other importance measures in data fusion, the proposed measure focuses on the degradation trend represented by the permutation entropy, instead of the information volume represented by the Shannon entropy. Then, a multiple fault feature variable fusion method based on the proposed importance measure is further proposed in the D-S evidence theory framework. Finally, a case study involving an oil analysis-based dataset from a power-shift steering transmission is carried out to investigate the superiority of the proposed method.**

Keywords-condition monitoring; Dempster-Shafter evidence theory; fault diagnosis; importance measure; permutation entropy

I. INTRODUCTION

Unexpected machine failure often leads to severe economic losses and safety problems that may sometimes have catastrophic consequences. Therefore, a machine should be monitored and maintained timely to prevent unexpected failures and extend health working hours. Currently, PHM techniques has become an important research field which can use condition monitoring (CM) data to estimate the condition of an operating machine [1]. In the PHM framework, it is commonly assumed that a machine failure will occur once the fault feature variable (the selected CM data, e.g., oil analysis data) cross a failure threshold [2]. Therefore, by comparing the failure threshold with the selected fault feature variable, the machine condition can be evaluated.

The development of CM instruments has leads to the use of various fault feature variable to monitor the machine condition. Most of the existing studies used a single type of fault feature variable to diagnose the machine condition. However, some recent studies have shown that using single type of fault feature variable is irrational, which may result in under- or over-diagnosis of the fault [3,4]. In addition, fault feature variable may be non-ideal due to measurement errors, which may result in inaccurate diagnosis results [5,6]. Thus, the fusion of multiple fault feature variable is one of the key issues to improve the performance of machine fault diagnosis. Driven by engineering practice, many researchers have proposed many methods for fault feature variable fusion. For example, Yan et al. fused multiple spectral oil data using a weighted average method in [3], and described the analysis procedure of oil field data and developed a machine degradation model using stochastic process by assuming the constructed health index is a valuable fault feature variable for characterizing the underlying degradation. In this paper, the rationality of using element concentration data for degradation modeling was also investigated. Recently, by maximizing the degradation trend of fault feature variable and minimizing the variance in system failure threshold, Liu and Gebraeel [19] proposed a more reasonable health index extracting method using a convex optimization function and then built system degradation model for a turbofan engine to determine the expected moment when a soft failure occurred. It is noted that the expected moment can be used as the system residual technique life, and further be set as the time to perform planned PM. In the most recent, Yan et al. [1] presented a CBM problem with selected oil field data to determine the optimal time of machine maintenance. In addition, the work in [1] presents a framework of using sampled oil field data for maintenance optimization. A review of the application of oil field data for LCM and CBM can be found in [2] and the references therein. However, among these methods, how to measure the relative importance of different fault feature variable from heterogeneous sources has become a challenge [7,8]. Therefore, the purpose of this paper is to propose a new importance measure that can be used for multiple fault feature variable fusion, and then design a new data fusion methodology for equipment condition monitoring, fault diagnosis, prognosis and maintenance.

Dempster-Shafer evidence theory is an admitted fault feature variable fusion method that can deal with fault feature variable and fault feature variable without known the priori information [9]. This useful property makes the evidence theory

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applied widely in many areas, such as risk analysis, failure evaluation, decision making, and so on [10]. In fact, not all fault feature variable shows the same degradation profile. Generally speaking, some fault feature variable that shows a significant increasing or decreasing trend is highly correlated with machine degradation, while others might not. When dealing with these fault feature variable that has different data types and from heterogeneous sources, the application of classical combination principle may not be suitable that will lead to an over- or under-diagnosed result [5]. To address this issue, some researchers presented many methods. Among these method, an effective approach is to measure the importance of different fault feature variable before fusing these fault feature variables [6-8]. During this years, some researchers presented many different metrics to measure the relative importance in fault feature variable fusion, for example, Murphy method [11], Jiang method [6]. However, how to measure the importance of different fault feature variables from heterogeneous sources in the evidence theory framework is still an important research topic.

Shannon entropy is a useful measure for measuring the amount of information contained in different data sets or their relative importance. It has been widely used in many fields, such as complexity measurement, multi-fault feature variable selection, and conflicting fault feature variable fusion [12,13]. For machine CM and diagnosis, the fault feature variable with a clear increasing or decreasing trend is more suitable [3-5]. Hence, the limitation of these existing literatures is that the weight of each fault feature variable is determined based on the amount of information expressed by Shannon entropy [6,7]. Therefore, this paper seeks to fulfill this gap by propose a new importance measure that can be used for fault feature variable fusion to characterize system degradation process that can be used for RL estimation. To address this issue, a new importance measure is proposed by measuring the increasing or decreasing trend, that can be expressed by permutation entropy [13,14], in the fault feature variable. With the proposed efforts, we expected to attain more accurate fault diagnose results.

The idea behind this work is as follows: If a set of fault feature variable shows more increasing or decreasing trend, this set of fault feature variable has more impact on the final fusion result. That is to say, the permutation entropy is utilized to define the weight factor in the fault feature variable fusion. This is of theoretical and practical useful to use information fusion method for fault diagnosis and, thus, is the main contribution of this paper. Based on the proposed importance measure, a new multiple fault feature variable fusion method is designed. First, based on the permutation entropy, the relative importance of each set of fault feature variable is measured. Then, use the Dempster's combination rule to fuse multiple fault feature variable. Finally, the proposed fault feature variable fusion method is verified by a case study in [15]

II. Development of the Fault feature variable Fusion Method

In this section, several key steps associated with the fusing of the multiple fault feature variable for fault diagnose, including the construction of the proposed importance measure are discussed.

A. The Proposed Importance Measure

Let us assume that the fault feature variable is represented by $X_{i,j} = \{x_{i,j} | i = 1,2, \dots, N; j = 1,2, \dots, M\}$, where $x_{i,j}$ is the fault feature variable of ith degradation data at t_j monitoring time. The relative frequency of each possible permutation type π is defined by:

$$p(\pi) = \frac{\#\{t | 0 \le j \le M-n, (x_{j+1}, \dots, x_{j+n}) \, has \ type \ \pi\}}{M-n+1}, \tag{1}$$

where n means the different numbers for the possible order types. The permutation entropy of order $n \ge 2$ can be determined by:

$$H(n) = -\sum p(\pi) \log p(\pi). \tag{2}$$

Among these entropies, 2! permutation entropy calculated in (3) has been widely used in engineering practice [13,14].

$$H(2) = -p\log p - (1-p)\log(1-p), \tag{3}$$

where p is the monotony probability of order $n = 2$.

According to information theory, $0 \le H(2) \le 1$, where the lower bound can be obtained for an increasing or decreasing fault feature variable series [16]. Thus, the weight of each basic probability assignment (BPA) in the frame of Dempster-Shafer evidence theory is defined in (4) based the proportion of permutation entropy.

$$w_i = \frac{1-H_i}{N-\sum_{i=1}^{N} H_i}. \tag{4}$$

Compared with Shannon entropy-based importance measure [6,7], the proposed method using the degradation trend to determine the weight of each BPA. In other words, we think smaller permutation entropy, greater weight.

B. The Proposed Fault feature variable Fusion Method

The fault feature variable fusion method is proposed using the proposed importance measure in the Dempster combination framework. The flow chart is shown in Figure 1.

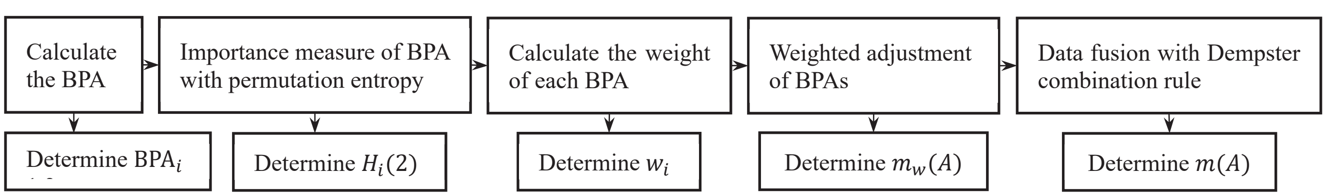

Figure 1. The flow chart of fault feature variable fusion method

1) Multiple fault feature variable modeling

We know that the multi-style fault feature variable that collected contains numerous noise like measurement errors. When use evidence theory to fault diagnose, the fault feature variable must be firstly modeled with BPA in evidence theory framework. It is noted that this step is a fundamental step that determines whether the fault diagnosis is correct or not.

2) Importance measure of BPA with permutation entropy

Using the BPA that obtained in the previous step, machine fault diagnose can then be achieved. However, we should first weight the importance between different fault feature variables. In this paper, we using the permutation entropy to measure the relative importance of the fault feature variable reports. Specifically, we use the 2! permutation entropy in (3).

3) Calculate the weight of each BPA

The weight of each BPA is positively associated with the monotonicity of each corresponding fault feature variable series [3-5]. Specifically, a smaller 2! permutation entropy value of BPA has a larger weight.

4) Weighted adjustment of BPAs

Using the weight calculated in the previous step, we can modify the BPA for next data fusion step. For each fault type diagnosis in our case study, the modified BPA can be calculated by the weighted average method [5-8]. Then, we can get the weighted BPA by the following formula:

$$m_w(A) = \sum_{i=1}^{n} w_i m_i(A). \tag{5}$$

5) Data fusion with dempster combination rule

We first assume that the fault feature variable number is n, according to the Dempster combination rule, we can get the diagnose result using (6) by calculating $(n-1)$ times.

$$m(A) = ((((m_w \oplus m_w)_1 \oplus m_w)_2 \dots \oplus m_w)_{n-2} \oplus m_w)_{n-1}(A), n \geq 2 \tag{6}$$

III. CASE STUDY

In this section, we use a case study to show the improved performance of our proposed method when used for data fusion and then used for fault diagnosis. To be specific, for the convenience of comparison, we use the case in the reliability test in [15]. Using this case study, we compare the diagnosis results of the proposed method with classical Dempster method [15], Murphy method [11] and Jiang method [6].

A. Overview of the Problem

Power-shift steering transmission (PSST) is a mechanical transmission that integrating mechanical, hydraulic, hydraulic, electronic, control and other multi-disciplines, achieving multi-speed and step-less steering. The power transmission technology in tracked armored vehicle has entered the stage of hydraulic mechanical integrated transmission with hydraulic transmission, hydraulic step-less steering, power shifting and automatic shifting. This type of device has high power density, high compactness and high reliability. Sexual characteristics, its function is strong, and its technical level is advanced. The PSST system we used in this paper is one of the core components of our military armored vehicles. Its performance directly affects the reliability and stability of the entire armored vehicle. It plays a key role in the normal performance of the tactical technical indicators of the armored vehicles. The military and economic losses caused by failure accidents are often immeasurable and is deadly. Therefore, from the perspective of reliability management, it is necessary to clarify how long the PSST system can continue to operate without the current time, that is, the time interval between the current time and the occurrence of the fault, that is, the life of the product is evaluated. To meet this demand, many life assessment, prediction and health management technologies have been developed in the fields of industry, defense, and aviation.

The failure modes of many components of the PSST can be traced back to the deterioration of product performance, such as the failure of the gear root crack leads to the failure of the gear, the wear of the gear transmission surface causes the gear transmission error, The wear of the bearing leads to a decrease in the transmission accuracy. Therefore, it is possible to describe the deterioration process of the device performance according to the device performance degradation monitoring data and predict the future development, further predict the remaining life of the product and provide guidance for the formulation of the maintenance strategy as appropriate, and reduce the occurrence of the failure. Therefore, product life prediction based on device performance degradation data has become an important research direction in the field of modern reliability management.

This paper considers the wear failure of a power-shift steering transmission (PSST) [3] that is monitored using regular oil analysis. The PSST was run to failure under the cyclic operation that was defined by the owner. The PSST was inspected every 2.5 motor-hour (Mh) during the operational life. Degradation data reports of one sample is shown in Table I. Detailed description of the PSST and sampling principles can be found in [3] and references therein.

TABLE I. FAULT FEATURE VARIABLE OF OIL ANALYSIS FROM PSST

Time/Mh	**Spectral oil data/ug/mm^3**							**Particle count /ISO4406**		**Iron content/ ug/mm^3**	**Oil viscosity/ mm^2/s**
67.5	ρ_{Fe}	ρ_{Cr}	ρ_{Pb}	ρ_{Cu}	ρ_{Si}	ρ_{Ni}	ρ_{Mn}	$d > 6um$	$d > 14um$	$1\sim200um$	100℃
	31.7	0.4	60.9	31.6	3.9	0.4	0.8	19	14	69	14.22

From the case study in [15], we know that there are six fault types for PSST fault diagnosis. To be specific, the recognized six fault types of a PSST are denoted as: $F_1 = \{\text{Valve failure}\}$, $F_2 = \{\text{Clutch failure}\}$, $F_3 = \{\text{Planetary gear set failure}\}$, $F_4 = \{\text{Seal ring failure}\}$, $F_5 = \{\text{Oil failure}\}$, $F_6 = \{\text{Gear wear failure}\}$, respectively.

We use various oil analysis techniques (Atomic emission spectrometers, Pods portable particle counters, etc.) equipped with fault diagnosis laboratories for the PSST system test and sports oil samples accumulated in the long-term, using oil pollution analysis and measurement technology. Study the characteristics of particulate pollutants in the life cycle of PSST, mainly the size, quantity and composition of pollutant particles. Provides raw data for theoretical and experimental studies of life prediction and health management for integrated transmissions and components. Then, we should decide with fault feature variable can used as fault feature variable for fault diagnose in PSST.

We summarize [15], and we know that: The performance and function of the hydraulic lubrication system of the vehicle integrated transmission play a key role in the reliability of the integrated transmission and the normal performance of the tactical technical indicators of the tank and armored vehicles. The oil analysis technology can analyze the physicochemical properties of the oil and the parameters such as the shape and size, material and content of the abrasive debris contained in the oil, and can characterize different friction stages (run-in period, normal wear period, severe wear period). Reflects different types of wear and tear (adhesive wear, abrasive wear, surface fatigue wear, corrosion wear, etc.). Therefore, the oil analysis technology can realize the location and process of wear of the device, the type of wear failure, the mechanism of wear, and the evaluation of oil quality; and it can realize wear condition monitoring and fault diagnosis without stopping or disassembling. Therefore, the use of advanced oil monitoring devices and analysis techniques to carry out research on oil pollution and performance degradation of integrated transmissions has important theoretical and practical value.

Therefore, the oil analysis data can be used as fault feature variable. To be specific, the spectral oil data, iron amount, the particle count data and the oil viscosity data can be used. On the other hand, these kinds of fault feature variable are commonly degradation data used for degradation modeling and planned maintenance optimization by many researchers, and they are regarded as tribodiagnostic data. In the case study of this paper and in [15], m_1, m_2, m_3 and m_4 denote the four types of degradation data respectively. And the result of variable reports modeled as BPAs is shown in Table II.

TABLE II. BPAS FOR FAULT DIAGNOSIS

	$\boldsymbol{F_1}$	$\boldsymbol{F_2}$	$\boldsymbol{F_3}$	$\boldsymbol{F_4}$	$\boldsymbol{F_5}$	$\boldsymbol{F_6}$
m_1	0.65	0.10	0.05	0.10	0	0.10
m_2	0.10	0.60	0.05	0.05	0.10	0.10
m_3	0.10	0.10	0.30	0.10	0	0.40
m_4	0.05	0.10	0.10	0.05	0.70	0

B. *Using the Proposed Method for Data Fusion*

In order to investigate the improved performance of our proposed for fault diagnose, we using the proposed method to solve the fault diagnose problem in [15] in this subsection. It is noted that five steps are included.

1) Data modeling with BPA

When use evidence theory to fault diagnose, the fault feature variables should be firstly modeled as BPAs. We should know that this step is a fundamental step that determines whether the fault diagnosis is correct or not. However, for the convenience of comparison, we adopted the fault feature variables and the BPAs from [15] directly, which can be found in Table I and II, respectively.

2) Permutation entropy based importance measure

Using the BPA that obtained in the previous step, machine fault diagnose can then be achieved. However, we should first weight the importance between different fault feature variables. In this paper, we using the permutation entropy to measure the relative importance of the fault feature variable reports. Specifically, we use the 2! permutation entropy in (3). And we can see the results in Table III.

2! Permutation entropies of each fault feature variable (unit:$\boldsymbol{bits}$)

BPA	$\boldsymbol{m_1}$	$\boldsymbol{m_2}$	$\boldsymbol{m_3}$	$\boldsymbol{m_4}$
$H(2)$	0.9685	0.4282	0.7865	0.9975

3) Calculate the weight

Using the calculated importance measure in Table III and (4), we calculate the weight of each BPA. Then, the weight for each BPA modification can be obtained. The result for each fault feature variable that can be used for BPA modification are shown as following:

$$w_1 = 0.0384, w_2 = 0.6979, w_3 = 0.2606, w_4 = 0.0031$$

4) Weighted adjustment

Using the weight calculated in the previous step, we modify the BPA for next data fusion step. Then, for each fault diagnosis in our case study, the modified BPA can be calculated in Table IV.

TABLE III. THE MODIFIED BPAS FOR FAULT DIAGNOSIS

	$\boldsymbol{F_1}$	$\boldsymbol{F_2}$	$\boldsymbol{F_3}$	$\boldsymbol{F_4}$	$\boldsymbol{F_5}$	$\boldsymbol{F_6}$
m_1	0.0250	0.0038	0.0019	0.0038	0	0.0038
m_2	0.0698	0.4187	0.0349	0.0349	0.0698	0.0698
m_3	0.0261	0.0261	0.0782	0.0260	0	0.1042
m_4	0.0002	0.0003	0.0003	0.0002	0.0021	0
$m(F_i)$	0.1211	0.4489	0.1153	0.0649	0.0719	0.1779

5) Data fusion using the combination rule

Using the result in Table IV, we then fuse the modified BPA obtained by our proposed method the Dempster combination rule with (6). Finally, the fault feature fusion results can be obtained, which are shown as follows:

$$m(F_1) = 0.0423, m(F_2) = 0.8495, m(F_3) = 0.0361,$$
$$m(F_4) = 0.0005, m(F_5) = 0.0014, m(F_6) = 0.0702$$

TABLE IV. DIAGNOSIS RESULT WITH DIFFERENT FUSION METHOD

Methods	$\boldsymbol{F_1}$	$\boldsymbol{F_2}$	$\boldsymbol{F_3}$	$\boldsymbol{F_4}$	$\boldsymbol{F_5}$	$\boldsymbol{F_6}$
Zheng's method [15]	0.0516	0.6344	0.1163	0.0008	0.0644	0.1325
Murphy's method [11]	0.0523	0.6727	0.0879	0.0012	0.0856	0.1003
Jiang's method [6]	0.0416	0.7138	0.0768	0.0248	0.0719	0.0693
Proposed method	0.0423	0.8495	0.0361	0.0005	0.0014	0.0702

C. Discussion

According to the fault diagnostic result in Step 5, it can be conculcated that F_2, clutch failure, is the recognized fault type, which indicate that the wet clutch in the PSST is failed. In order to compare the diagnose result from previously proposed methods in [6,11,15], the diagnosis results based on different fusion methods are shown in Table V.

From Table V we can see that although the diagnosis results based on different method in [6,11,15] all recognize the fault type F_2, the proposed method has the highest belief level (84.95%) on the recognized fault type F_2. It is concluded that our proposed method has a strong ability in dealing with multiple fault feature variable fusion by using permutation entropy to measure the degradation trend of an PSST system.

IV. Conclusions

fault diagnosis of a system is an important research topic in improving the safety of the operation and reducing the economic losses afterward. For the PSST system we used in the case study, its reliability is a prerequisite for ensuring the maneuverability and flexibility of tracked armored vehicles, and is an important guarantee for improving the rapid response capability and the survivability of the battlefield. With the increasingly fierce competition and the rapid development of industrial technology in the new world, the mechanical power transmission system of modern military armored vehicles has shown a large-scale, high-complexity and high-efficiency development trend.

Therefore, the reliability and safety of the vehicle PSST systems have received extensive attention. Therefore, in order to ensuring the PSST system safely, a permutation entropy-based importance measure and then a weighted multiple fault feature variable fusion method is proposed in this article in the framework of Dempster-Shafer evidence theory. Using this proposed method, an accurate fault diagnose can be achieved. This useful property can do a benefit for ensuring a long-term reliable operation.

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