

## Condition Monitoring and Fault Diagnosis for Marine Diesel Engines using Information Fusion Techniques

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### Introduction

Marine diesel engines are crucial for vessels. The normal operation of the marine diesel engine is essential for the safety of voyages. However, exposed in harsh environment, the marine diesel engines are prone to break down [1–3], leading to terrible marine accidents. It is therefore imperative to monitor the condition of marine diesel engines and hence discover impending failures. By doing so, the scheduled completion and efficiency of a trip can be ensured.

Machinery condition monitoring and fault diagnosis (CMFD) technique initially emerged at the end of 1960s. With decades of development, many CMFD methodologies have been proposed for a various industrial applications. In the marine engineering, popular CMFD methods include the performance parameter monitoring, vibration analysis, and oil analysis, etc [1]. The vibration analysis is among the most successful method for the marine diesel engine fault diagnosis [2], and numerous signal processing techniques have been proposed to analyze the vibration signals of the engines. Advanced signal processing techniques, including short time Fourier transform (STFT) [4], wavelet transform (WT) [2], Hilbert-Huang transform (HHT) [5], etc., are applicable for the analysis of mechanical vibration signals. However, these mentioned methods of the second approach in the last section can handle one-dimensional signal only, i.e. vibration signal from one sensor only. Depending upon different machines structures and the location of a fault, analyzing the vibration signals in more than one direction may become significant to enhance the fault detection performance. For this reason, multiply sensors installed at different directions/locations are employed in the CMFD process to measure the vibration

information from different perspectives. It is crucial to make full use of multi-sensor data. Thus, how to efficiently analyze the signals from a set of sensors using proper information fusion techniques becomes a key issue.

The independent component analysis (ICA) is powerful to find a suitable representation of multivariate mixtures. The ICA algorithm has been proven to be very efficient to separate independent sources contained in the observations from multi-channel sensors. As a result, the ICA is capable to make full use of multiply sensors in the CMFD procedure. Since the vibration of the engine body in nature is the mixture of the diesel cylinder-piston movement, fault components excitation, and background noise and so on, by the data fusion of ICA the characteristics of the fault components excitation can be separated from the measured signals of multiply sensors [3]. Hence, the fault detection can be enhanced. Guo and Tan [6] used the ICA to exclude noise for rotor systems, but the fault detection performance was not presented in their work. Li et al [7] adopted the ICA to extract distinct feature for the rotor fault diagnosis in the speed-up and speed-down process. Albarbar et al [8] developed the ICA based scheme for the Air-borne acoustic based condition monitoring of diesel engine fuel injection. Gao et al [9] investigated the ICA based preprocessing method for vibration signals on cylinder head of diesel engine. However, very limited work has been done for the CMFD processing of marine diesel engines. Hence, the outcomes of the ICA should be tested for the condition monitoring and fault diagnosis of marine diesel engines.

To develop a diagnostic system that can fuse multi-channel sensor signals, a new ICA-based diagnostic system for marine diesel engines is proposed in this work. The FastICA algorithm [10] was combined with the short time Fourier transform (STFT) and Fuzzy neural network (FNN)

to form an intelligent CMFD system. A series of experiments have been conducted on a real ship to verify the diagnosis performance of this new system. The analysis results show high efficiency of the proposed information fusion based diagnostic method.

### Description of proposed information fusion method

As mentioned above, the integration of the ICA, STFT and FNN has been proposed for the CMFD of marine diesel engines. The ICA was first used to fuse multiply sensor signals. The STFT was then adopted to extract the time-frequency characteristics of the ICA outputs and the principal component analysis (PCA) was used to reduce the feature dimension. Lastly, the FNN was employed to identify the engine fault patterns. The theories of STFT and PCA can refer to [4] and [2], respectively. The ICA algorithm and FNN structure are briefly introduced below.

*A. Independent component analysis (ICA).* Due to the interference of the structural path of a fault, a measured vibration signal may be distorted to a certain degree. Fortunately, the ICA can fuse the multi-channel observations and find a suitable representation [10]. The ICA is defined as follows [10]

$$X = A \cdot S + \delta, \quad (1)$$

where,  $X = [x_1 \ x_2 \ \dots \ x_n]^T$  is an observation matrix, and  $n$  is the number of sensors.  $S = [s_1 \ s_2 \ \dots \ s_m]^T$  is the unknown statistical independent matrix with  $m$  independent components.  $A$  is the mixing matrix and  $\delta$  is noise. The task of ICA is to obtain the inverse matrix  $W$  of  $A$ . Then the independent components could be obtained by  $\hat{S} = W \cdot X$ . Thus, the desired fusion signal can be got by checking the output of ICA. The FastICA is one of the most popular algorithms to estimate  $W$ . It uses negentropy to present the following iteration [10]

$$W(k+1) = E\{Xg(W(k)^T X)\} - E\{g'(W(k)^T X)\}W(k), \quad (2)$$

where  $g(\cdot)$  is a nonlinearity function, usually choose the Gaussian function. By the minimum of the negentropy,  $W$  can be obtained.

*B. Fuzzy neural network (FNN).* Fuzzy algorithm is very suitable for the fault pattern recognition because it adopts human-friendly logic. Since the membership functions of the Fuzzy model are often selected by human experiences, the fuzzy inference processing may be lack of self-adaptation. To solve this issue, the artificial neural network (ANN) has been introduced into the Fuzzy model to optimize the membership functions [11].

The FNN consists of input layer, fuzzy layer, hidden layer and output layer. The fuzzy layer, hidden layer and output layer are connected by the weights  $\omega_{lj}$  and  $\omega_{kl}$ , respectively. The input variables  $P = [p_1, p_2, \dots, p_i]^T$  is fuzzified in the fuzzy layer to get fuzzy membership values

$$\begin{cases} f_j = \mu_{A_{ij}}(p_i) = [f_{1j}, f_{2j}, \dots, f_{ij}]^T, \\ \mu_{A_{ij}}(p_i) = \exp\left[-\left(\frac{p_i - a_{ij}}{b_{ij}}\right)^2\right]. \end{cases} \quad (3)$$

where  $a_{ij}$  is the center of membership function and  $b_{ij}$  is the width. The output of the fuzzy layer is  $F = [f_1, f_2, \dots, f_j]$ . In the hidden layer, the fuzzy rule of the  $l$ th neuron is

$$y_l(f_j) = a_{lj} x_j. \quad (4)$$

The fourth layer outputs the fuzzy decision of the FNN. By the supervised training processing, the FNN can provide high performance to find the inner relationship between the input features and the fault patterns.

The diagnostic principle of the proposed CMFD system is schematically shown in Fig. 1.

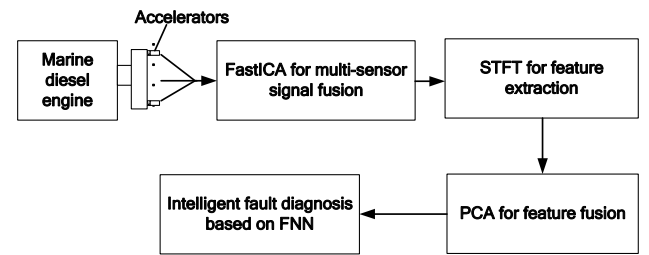


Fig. 1. The diagnostic principle of the proposed vibration analysis

### Experimental results

Experiments have been conducted under the normal and faulty conditions of the diesel engine in a real ship. The valve rocker arm broke in the faulty condition. The arrangement of the accelerators and speed encoder is shown in Fig. 2. Four-channel vibration sensors are fixed on the engine body to collect different direction vibrations.

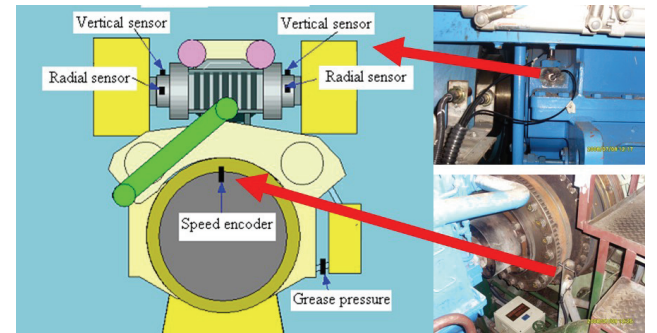


Fig. 2. The arrangement of the vibration a sensors

Fig. 3 shows the signal fusion results by FastICA using the four-channel original vibration under broken valve rocker arm. The independent component signal in Fig. 3(a) presents the cyclical shocks of the piston-cylinder movement, so we use this signal to diagnose the engine fault. Figs. 4 and 5 show the time-frequency spectra of the selected independent component under faulty and normal conditions, respectively.

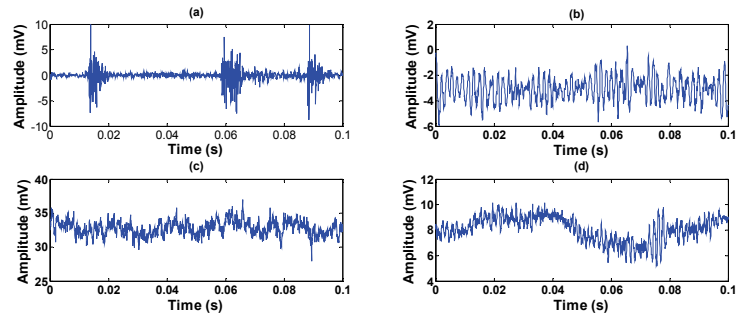


Fig. 3. The estimated independent components by the FastICA fusion under faulty condition

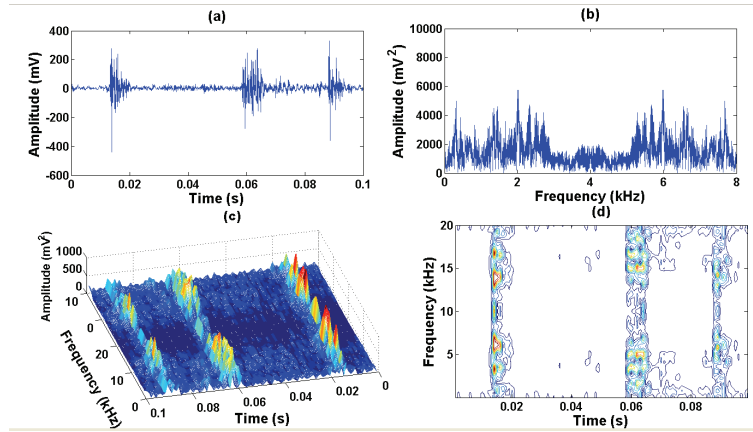


Fig. 4. The time-frequency spectra of the selected independent component under faulty condition: (a) time spectrum, (b) frequency spectrum, (c) STFT time-frequency spectrum, and (d) STFT time-frequency contour map

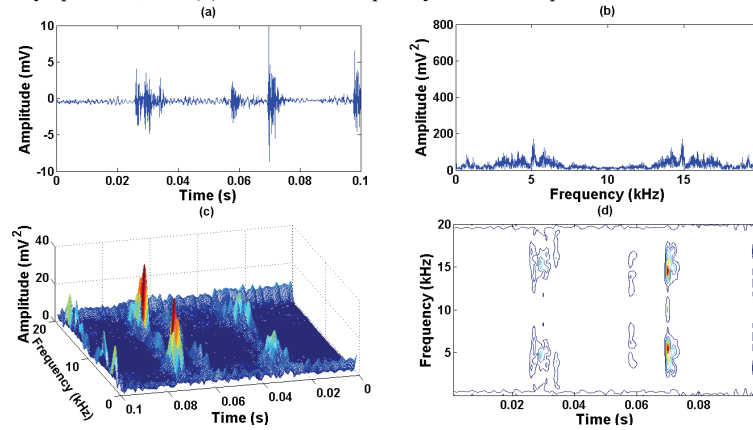


Fig. 5. The time-frequency spectra of the selected independent component under normal condition: (a) time spectrum, (b) frequency spectrum, (c) STFT time-frequency spectrum, and (d) STFT time-frequency contour map

It can be seen from Fig. 4 and Fig. 5 that the vibration energy under faulty condition is higher than normal condition, and the energy range of the peak values under faulty condition is larger than normal condition. That means the energy information can be used to distinguish the normal and faulty engine states. Hence, the energy values of the time bands [0.01 s 0.02 s], [0.025 s 0.035 s], [0.048 s 0.052 s], [0.055 s 0.065 s], [0.068 s 0.072 s] and [0.085 s 0.095 s] were calculated as the original feature vector. Each energy value is the sum of the energies along the frequency axis. The interval of the computation is 0.001 s, and hence original feature vector contained 50 elements. Then the PCA was adopted to fuse the original feature vector from 50 dimensions into 3 principal components. By doing so, redundant features can be eliminated. 100 samples for each engine state were prepared in this work. The fault pattern recognition results

of the FNN are listed in table 1, where the proposed method has been compared with non-fusion pre-processing.

Table 1. Fault pattern recognition results of type 1 by PNN

Detection rate (%)		Training time (s)	
Without ICA	With ICA	Without PCA	With PCA
84.5	90.5	4.83	1.32

## Conclusions

It can be seen from table 1 that the fault recognition rate of the proposed method is better than that without ICA based signal fusion, and the feature fusion using PCA can reduce the computation of the FNN. This is because the ICA has made full use of the four vibration sensors, and the PCA has obtained distinct fault features in a low data

dimension to speed up the training of FNN. These two advantages have benefited the fault pattern identification and hence increase the detection accuracy.

Taking the advantages of new signal processing techniques, this paper has reported the new development of condition monitoring and fault diagnosis (CMFD) system for marine diesel engines using the combination of ICA, STFT, PCA and FNN. The experiment tests in a real ship show that the information fusion can enhance the fault feature extraction and the newly proposed information fusion based fault diagnosis method is reliable and feasible for fault diagnosis of marine diesel engines.

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**Zhixiong Li, Xiping Yan, Zhiwei Guo, Yuelei Zhang, Chengqing Yuan, Z. Peng. Condition Monitoring and Fault Diagnosis for Marine Diesel Engines using Information Fusion Techniques // *Electronics and Electrical Engineering*. – Kaunas: Technologija, 2012. – No. 7(123). – P. 109–112.**

The structural complexity of marine diesel engines and the failure transmission path significantly influence the quality of a measured vibration signal. A set of accelerometers have been involved in the condition monitoring and fault diagnosis (CMFD). To make full use of multi-channel sensor signals, a new information fusion method is proposed for the CMFD of marine diesel engines in this paper. For the signal fusion, the independent component analysis (ICA) was firstly adopted to separate useful source signal close to the engine vibration characteristics of the fault components from multi-channel sensors. Then the short time Fourier transform (STFT) was applied to the fault feature extraction and the principal component analysis (PCA) was used to fuse the feature space from a high dimension into a very low one. Followed, a Fuzzy neural network (FNN) classifier was employed to identify the engine faults. The real vibration data measured on a ship using four-channel sensors was used to evaluate the proposed method. The experimental diagnostic results demonstrate that the developed diagnostic method captures distinct time-frequency features of the vibration signals for monitoring the engine health condition with a fault detection rate of 90.5%. Moreover, the performance of the proposed method is superior to that without information fusion processing. Thus, the proposed method is feasible and available for the CMFD of marine diesel engines. III. 5, bibl. 11, tabl. 1 (in English; abstracts in English and Lithuanian).

**Zhixiong Li, Xiping Yan, Zhiwei Guo, Yuelei Zhang, Chengqing Yuan, Z. Peng. Laivų dyzelinių variklių būsenos monitoringas ir gedimų diagnostika taikant informacijos sintezės metodus // *Elektronika ir elektrotechnika*. – Kaunas: Technologija, 2012. – Nr. 7(123). – P. 109–112.**

Laivo dyzelinio variklio struktūrinis kompleksiskumas turi įtakos matuojamo vibracijos signalo kokybei. Įbūsenos monitoringui ir gedimų diagnostikai (BMGD) buvo panaudotas akcelerometrų rinkinys. Siekiant reikiamai panaudoti daugiakanalių jutiklių signalus buvo pasiūlytas naujas informacijos sintezės metodas, skirtas laivų dyzelinių variklių BMGD. Neraiškiosios logikos neuroninių tinklo klasifikatorius buvo panaudotas variklio gedimams identifikuoti. Realios vibracijos laive duomenys, gauti naudojant keturių kanalų jutiklius, buvo panaudoti pasiūlytam metodui vertinti. Eksperimentiniai diagnostikos rezultatai rodo, kad sukurtas diagnostikos metodas laidžia surasti išskirtines laikines-dažnines vibracijos signalų ypatybes stebint variklio būseną, kai gedimų detektavimo lygis 90,5 %. Pasiūlytasis metodas tinka laivų dyzelinių variklių BMGD. II. 5, bibl. 11, lent. 1 (anglų kalba; santraukos anglų ir lietuvių k.).