Sheng Chenxing[1, 2], Tian Zhe[1, 2], Zhang Yuelei[1],

[1] Key Laboratory of High Performance Ship Technology of Ministry of Education (Wuhan University of Technology), Wuhan 430063, China
[2] Reliability Engineering Institute, School of Energy and Power Engineering, Wuhan University of Technology, Wuhan 430063, China

Nonlinear Blind Source Separation of Multi-Sensor signals for Marine Diesel Engine Fault Diagnosis

***Abstract**. Marine diesel engines are the heart of the ships. They provide the power for the normal propulsion of the vessels. Any unexpected failures occurred in the marine diesel engines may lead to terrible accident. It is therefore imperative to monitor the marine diesel engines to prevent impending faults. In the present work, a new defect detection method for the marine diesel engines using the artificial intelligence has been proposed. The vibration signals of the marine diesel engine were recorded by the multi-channel sensors. The nonlinear independent component analysis (NICA) was adopted as the data fusion approach to find the characteristic vibration signals of the marine diesel engine fault from the multiply sensor collections. Then the Empirical Mode Decomposition (EMD) was employed to extract the feature vector of the fused vibration signals. Lastly, the Genetic Algorithm-Chaos and RBF neural network was used to recognize the fault patterns of the marine diesel engine. The experimental tests were implemented in a real ship to evaluate the effectiveness of the proposed diagnosis approach. The diagnosis results have showed that distinguished fault features have been extracted and the fault identification accuracy is satisfactory. In addition, the classification rate of the proposed method is superior to the traditional linear ICA based methods.*

***Streszczenie.** Wykorzystano nieliniową niezależną analizę składników NICA do diagnostyki wibracji silnika Diesla. Zastosowano metodę empirycznej dekompozycji EMD do separacji sygnałów. Następnie wykorzystano sieci neuronowe i algorytm genetyczny do identyfikacji uszkodzeń. (**Wykorzystanie nieliniowej ślepej separacja sygnałów wielu czujników do diagnostyki silnika Diesla w napędach okrętowych**)*

Keywords: Marine diesel engine, fault diagnosis, nonlinear ICA, GA, Chaos.
Słowa kluczowe: silniki okrętowe Diesla, diagnostyka, ślepa separacja, multi-czujniki.

Introduction

As widely known, the marine diesel engine is one of the important electrical equipment in marine propulsion system which has great significance for ensuring the security of ship operation. According to some relevant statistics, the over voltage and low voltage of the generation, the failures in the relay protect equipment and the frequency-power automatical control unit are the main fault of the marine diesel engine, which account for a large proportion in general fault. In recent years, the monitoring method based on the vibration signal of the marine diesel engine was put forward at home and abroad [1]. The method can evaluate the situation of marine diesel engines through the analysis of the vibration signal characteristics. Up to date, many methods have been proposed for the marine diesel engine fault diagnosis based on vibration signal, such as wavelet transform [2], Hilbert-Huang [3] and so on. They have been combined with intelligent neural networks to provide accurate fault detection [3-7]. However, the problem is that due to the lack of the training fault samples, the networks easily fall into the local minimum and training time is long. These disadvantages restricted the artificial neural network (ANN) in fault diagnosis of further applications and development. Since genetic algorithm (GA) has good global search capability, researchers have adopted it for optimizing neural network, and obtain the satisfactory structure of ANNs. However, GA suffers from the premature convergence. Therefore, in order to use GA for optimization the structure of the neural network model, and to eliminate GA precocious defects at the same time, a new method based on Chaos-genetic algorithm (GA-Chaos) and RBF neural network is presented in this paper. The chaotic technology is used improve GA optimization process and avoid the early-maturing problem, and hence the RBF network structure can be optimized, thus the fault detection rate can be improved.

On the other hand, the data fusion of multiply sensors is essential for reliable fault feature extraction. The vibration signals are often submerged in a large amount of redundant data. The blind source separation (BSS) algorithms are widely used to separate independent components in a data set based on its statistical properties. The independent component analysis (ICA) based BSS procedure has been successfully applied for independent component extraction in order to remove the noise signals mixed into the original data. In 1987, Giannakis, et al [8] proposed the identification ability of the blind source separation (BSS) problem, and introduced the three order statistics into implementation of the BSS. Following in 1991, Jutten and Herault [9], Sorouchyari [10], Comon [11] have published three important papers about the BSS in the journal of Signal Processing, which was the milestone of the BSS development. To some degree, the linear ICA (i.e. Fast ICA, etc.) can solve the nonlinear cases. However, when the nonlinearity increases, the linear ICA cannot work anymore. For nonlinear mixing models, many difficulties occur because of the complexity of nonlinear characteristics. In addition, there is no guarantee for the uniqueness of the solution of nonlinear BSS. The nonlinear BSS method using the ANN based ICA has hence been proposed to deal with the underlying nonlinear behavior of the data. Deco [12] proposed the volume-conserving nonlinear transforms. Pajunen et al [13] presented the self-organizing map (SOM) to extract independent sources from nonlinear mixture. Burel [14] proposed a nonlinear BSS algorithm using PNN. Taleb et al. [15] studied the entropy-based direct algorithm for BSS in post nonlinear mixtures. Tan [16] proposed the RBF neural network based ICA to solve the nonlinear BSS problem. It is concluded that the RBF neural network based ICA is very effective in the nonlinear BSS because the use of the mutual information and accumulation decreases the uncertainty of the solution caused by the nonlinearity. Hence, it is reasonable to further develop the RBF based ICA to validate its outcomes in the fault diagnosis of marine diesel engines.

In order to enhance the fault detection rate, a new approach is presented for the marine diesel engine fault diagnosis in the marine power system. The vibration signals were firstly fused by the NICA, and vibration features were extracted by EMD. Then the GA-Chaos-RBF neural network was used to learn the fault feature vector that matches with the fault patterns of the marine diesel engine. Finally, the fault experiments were carried out in a real ship propulsion system. The analysis results show effectiveness of the proposed method.

Description of proposed algorithm

Before extracting the characteristics of the vibration signals of the marine diesel engine under different working conditions, it is better to fuse the multi-channel sensor's data into the one that is close to the real vibration of the marine diesel engine. For this reason, the NICA has been introduced to the data fusion of the multi-channel sensors. Then the EMD is used to extract useful features of the fusion data. Lastly, the GA-Chaos-RBF detection model is proposed to identify the plant operation state. The workflow of the diagnosis is shown in Fig. 1. A brief description of the NICA is presented below, and the theories behind the EMD and GA-Chaos-RBF can refer to Refs. [17, 18].

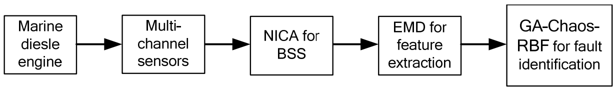

Fig. 1. The workflow of the proposed diagnosis procedure

Nonlinear BSS

The nonlinear BSS is the extension of the linear BSS algorithm. It first uses the ANN to solve the reversal of the nonlinear mixing model, and then employs the traditional linear ICA to find the independencies. The mathematics model, of the nonlinear BSS mixing is expressed as

$$\begin{cases} x = As \\ m = f(x) \\ n = g(m) \\ y = Wn \end{cases} \tag{1}$$

where s is the source signals, x is the linear mixing, m is the nonlinear mixing, n is the nonlinear de-mixing, and y is the linear de-mixing. $f(\cdot)$ is the nonlinear mixing function, and $g(\cdot)$ is the nonlinear de-mixing function. A is the linear mixing matrix, and W is the linear de-mixing matrix. The system diagram of the nonlinear BSS is shown in Fig. 2. In this paper, the RBF neural network has been adopted to act as the nonlinear de-mixing solver. The detail of the RBF based ICA for the nonlinear BSS can be referred to Tan [16].

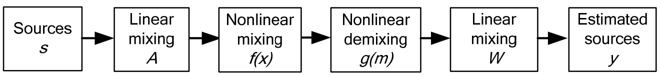

Fig. 2. The system diagram of the nonlinear BSS

Experiments and results

The experiments of the simulated faults have been carried out in a real ship power system, the "Changjing 2" dredge (see Fig. 3). The main diesel engine is the DAIHATSU 12DKM-36F with a rated power 6300 kW (see Fig. 3). The vibrations are measured under five different conditions: pattern A－normal, pattern B－oil leakage, pattern C－oil supply insuficiency, pattern D－cylinder fault, and pattern E－piston fault.

Four-channel acceleration sensors are adsorbed on the marine diesel engine through permanent magnet, and the surface of each permanent magnet is coated with insulation lacquer which can ensure the sensor shell float and resist the electromagnetism interference. The vibration data is collected every other 5 minutes under 600 rpm of the engine speed.

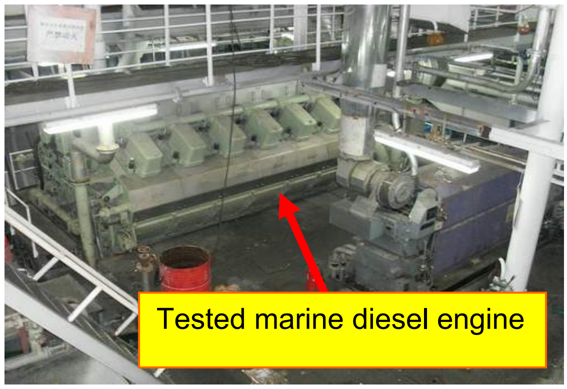

Fig. 3. The experimental diesel engines

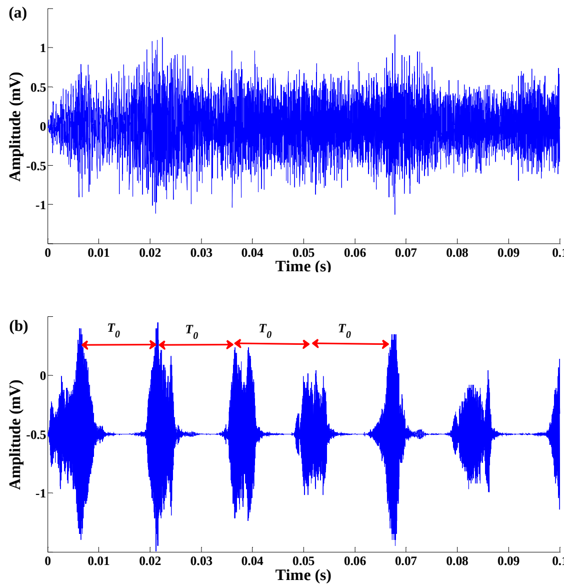

Fig. 4. The time spectra: (a) original vibration signal and (b) NICA separated source.

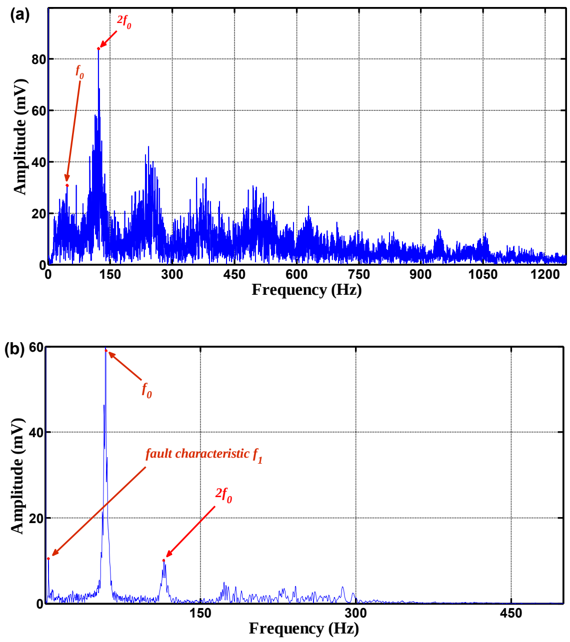

Fig. 5. The frequency spectra: (a) original vibration signal and (b) NICA separated source.

Feature extraction of the vibration signals

The vibration signal recorded under oil leakage of the generation is used to evaluate the performance of the ICA based data fusion. Figs. 4-5 show the fusion result of the vibration signals, where T_0 and f_0 are the basic operation period and frequency of the diesel generator, respectively, and f_1 is the fault frequency.

It can be seen from Figs. 4-5 that by the use of NICA fusion, sensitive frequency information is presented at the fault frequency, f_1. In contrast to the original signal, the period T_0 is clear in the fused vibration signal. That is to say, more reliable features of the fault signal can be capture by the EMD. Six IMFs have been extracted in this work and the kurtosis of each IMF has been calculated as the input feature vector of the RBF to detect the marine diesel engine faults.

Fault pattern identification

As described in Section Ⅱ, the GA-Chaos-RBF is used to find the inner collection between the fault features and the marine diesel engine states. The inputs of the RBF are the six kurtosis values. The desired output of the RBF is as: [0 0 0] stands for pattern A, [0 0 1] stands for pattern B, [0 1 0] stands for pattern C, [1 0 0] stands for pattern D, and [1 0 1] stands for pattern E. In the GA-Chaos optimization, the initial λ is arranged from [0 50], and initial σ is arranged from [0 10]. After the optimization, the optimal λ = 34.38 and σ = 0.71.

20 samples of each fault condition have been collected and there are 100 samples in total. Half of the samples are used to train the RBF, and the remainders are used to test the trained RBF. A portion of the fault diagnosis results for the marine diesel engine is shown in table 1. The fault detection performance of the RBF model for marine diesel engine is given in table 2. In the fault pattern recognition, the NICA-GA-Chaos-RBF, NICA-RBF and GA-Chaos-RBF have been compared with respect to the diagnosis performance. The fault detection rate, uncertain decision and time consumption have been compared. Table 3 gives the comparison of the NICA and ICA.

Table 1 shows that the proposed method can enhance the fault detection precision. The use of the NICA and GA-Chaos can decrease the false alarm. It can be seen in table 2 that the RBF testing accuracy is increased significantly after the BSS fusion and GA-Chaos optimization. Moreover, the false detections have been decreased by 2.53% or better when conduct the GA-Chaos processing, and the detection rate of NICA can be enhanced by 1.6% comparing wit ICA processing.

Table 1. A portion of the fault detection results

Test number	Diagnostic approach	Diagnosis output			Desired output	Detection result	Desired result
	GA-Chaos-RBF	0.0431	0.0852	0.0653	[0 0 0]	Pattern A	Pattern A
1	NICA-RBF	0.0421	0.0564	0.0518	[0 0 0]	Pattern A	Pattern A
	NICA-GA-Chaos-RBF	0.0255	0.0085	0.0156	[0 0 0]	Pattern A	Pattern A
	GA-Chaos-RBF	0.4521	**0.8916**	**1.0215**	[0 0 1]	***Uncertain***	Pattern B
2	NICA-RBF	0.5017	**0.8825**	**0.9564**	[0 0 1]	***Uncertain***	Pattern B
	NICA-GA-Chaos-RBF	0.1542	0.4946	**1.0248**	[0 0 1]	Pattern B	Pattern B
	GA-Chaos-RBF	0.1638	**0.9541**	**0.8326**	[0 1 0]	***Uncertain***	Pattern C
3	NICA-RBF	0.0946	**1.1577**	0.4543	[0 1 0]	Pattern C	Pattern C
	NICA- GA-Chaos-RBF	0.3278	**1.3252**	0.3654	[0 1 0]	Pattern C	Pattern C
	GA-Chaos-RBF	0.4236	**0.9841**	0.2589	[1 0 0]	***Pattern C***	Pattern D
4	NICA-RBF	**1.0110**	0.4568	**0.8597**	[1 0 0]	***Pattern E***	Pattern D
	NICA-GA-Chaos-RBF	**1.0251**	0.5412	0.4127	[1 0 0]	Pattern D	Pattern D
	GA-Chaos-RBF	**2.5644**	0.7221	0.6515	[1 0 1]	***Uncertain***	Pattern E
5	NICA-RBF	0.0142	0.2451	**0.9754**	[1 0 1]	***Pattern B***	Pattern E
	NICA-GA-Chaos-RBF	**1.1238**	0.4123	**1.0124**	[1 0 1]	Pattern E	Pattern E

Table 2. The fault detection performance of different diagnosis approaches

NICA-GA-Chaos-RBF		ICA-GA-Chaos-RBF		NICA-RBF		ICA-RBF	
Detection rate	False decision	Detection rate	False decision	Detection rate	False decision	Detection rate	False decision
96.7%	1.02%	95.1%	1.13%	90.5%	3.36%	88.9%	3.64%

Conclusion

The marine diesel engine in the marine propulsion system provides the electricity supply for a ship. Any failures may lead to great losses of the trip. Therefore, it is critical to detect the early faults and protect the operation security of the marine diesel engine. In order to improve the fault detection accuracy, a new detection method based on NICA-GA-Chaos-RBF is proposed in this paper. Innovation points are that the new method adopts the nonlinear ICA algorithm to fuse multiply sensors into one optimal signal that represents the fault characteristics. Moreover, the GA-Chaos is employed to optimize the RBF parameters. Hence, satisfactory RBF detection rate can be obtained. Experimental results have validated the effectiveness of this new method. The optimized RBF has high accuracy of classification, and its performance is superior to the linear ICA models. Hence, the proposed method is feasible for the fault diagnosis of the marine diesel engine.

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***Corresponding Author**: A. Prof./Dr. Chenxing Sheng, School of Energy and Power Engineering, Wuhan University of Technology, Heping Street, 1040#, Wuhan, 430063, P. R. China, E-mail: schxing@yeah.net.*

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