Performance Assessment and Fault Diagnosis for Hydraulic Pump Based on WPT and SOM

Bei Jikun, Lu Chen[1] and Wang Zili
School of Reliability and Systems Engineering, Beihang University, China
Science & Technology on Reliability & Environmental Engineering Laboratory, Beijing, China

E-mail: luchen@buaa.edu.cn

Abstract. Hydraulic pump is the heart of hydraulic system, therefore a real-time condition monitoring for hydraulic pump is crucial to the reliability of the entire system. In this study, a method for performance assessment and fault diagnosis to hydraulic pump based on wavelet packet transform (WPT) and Self-organizing mapping (SOM) neural network is proposed. First, WPT is utilized to decompose the vibration signal into components, energy of each component is extracted and normalized to form the feature vector. Second, SOM neural network, trained only by normal data, is used to map feature vectors into Minimum Quantization Error (MQE), which is then normalized into confidence values (CV). Performance assessment is accomplished by tracking the trends of CVs. Finally, when faults occur, SOM, trained by both normal and faulty samples, is employed to classify the faults into different groups, which delegates different fault modes of the hydraulic pump. In addition, Taguchi method is used to reduce the redundant features and extract the principal components to ensure the effectiveness of the approach. A case study based on the vibration dataset of test plunger pump rig is conducted to demonstrate that the proposed method is able to assess the performance of hydraulic pump and diagnose faults suitably.

1. Introduction

Hydraulic pump is a crucial component in hydraulic system, its performance directly determines the hydraulic pressure, which reflect status of the entire system. Unexpected faults of pumps usually cause enormous losses, however, a condition monitoring based process can give a pre-warning, then repairs or replacements can be taken at the earliest or most convenient time with the minimum loss of productivity.

Faults of hydraulic pumps are generally accompanied with changes in vibration signal. Thus, vibration diagnosis is important in this field and is also the foremost topic of interest for researchers. Considering the complexity of hydraulic pump and the working conditions, data-driven methods are usually applied to online fault diagnosis. Nowadays, several data-driven methods exist for condition monitoring, such as principal component analysis, discriminant analysis and cluster analysis, as well as artificial neural networks.

Self-organizing mapping (SOM) network, a data-driven neural network proposed by Kohonen, has been broadly used in diagnostic applications dealing with data classification, and the Minimum Quantization Error (MQE) calculated by SOM offers a method for the assessment of performance.

The advantage of SOM is that: (1) its training process, without predetermined supervision, provides favorable recognition rate to unknown signal; (2) the topology of its network is self-adaptive, which means self-stabilization and immunity from interference.

However, send the original vibration signal of hydraulic pump into SOM seems complicated in computation, and usually causes unsatisfactory results, therefore, a feature vector, carrying substantive characteristics of the signal is needed in this approach. Traditional signal processing techniques, including time-domain and frequency-domain analysis, are based on the assumption that the processing signals are stationary and linear. Unfortunately, vibration signals of abnormal hydraulic pump are both nonlinear and non-stationary. Here, wavelet packet transform (WPT), introduced by

[1] To whom any correspondence should be addressed.

Coifman [1], provides an effective way to process nonlinear and non-stationary signal. It decomposes a signal repeatedly into successive low and high frequency components using a recursive filter-decimation operation. After decomposition, the energy of each component is extracted and normalized to form feature vector, which represents the status of hydraulic pump.

Additionally, to ensure the effectiveness of the approach and get rid of the well-known “garbage in, garbage out” problem, Taguchi method is employed to determine the key features from the initial feature set and screen out unsuitable features.

The main purpose of this study is to propose a method for performance assessment and fault diagnosis to hydraulic pump based on WPT and SOM. In this method, WPT and energy extraction is combined to extract feature; SOM based MQE, optimizing by Taguchi method, is then employed to calculate confidence value (CV), which represented performance of hydraulic pump; finally, when faults occur, SOM, trained by both normal and faulty samples, is employed to classify the faults into different fault modes.

This paper is organized as follows: Section 2 introduces WPT, SOM, Taguchi method and the proposed method for fault diagnosis and performance assessment; Section 3 describes the case studies performed to validate the method; and Section 4 gives conclusions and some ideas for future work.

2. Methodology

2.1. Signal processing by wavelet packet transform

WPT is considered as a generalization of the wavelet transform, the decomposition is performed on both low and high frequency components of any waveform [2]. After the decomposition of the *j*th level, the original signal $f(t)$ can be constructed by the sum of 2^j components as:

$$f(t)=\sum_{i=1}^{2^j} f_j^i(t) \tag{1}$$

where $f_j^i(t)$ is the wavelet packet component signal that can be expressed by a linear combination of wavelet packet functions as:

$$f_j^i(t)=\sum_{k=-\infty}^{\infty} c_{j,k}^i \psi_{j,k}^i(t) \tag{2}$$

where i, j and k are integers and defined as the modulation, scale and translation parameter, respectively; $c_{j,k}^i$ is the wavelet packet coefficients, $\psi_{j,k}^i(t)$ is wavelet packet function.

2.2. Feature extraction by energy extraction

Here, feature extraction is performed by energy extraction, each component $c_i(t)$ is processed with:

$$E_i=\int_0^{+\infty}\left|c_i(t)\right|^2 dt \tag{3}$$

where E_i is the energy of each component, normalized it as below:

$$T_i^{"}=\left(E_1\left(\sum_{i=1}^{n} E_i\right)^{-1}, E_2\left(\sum_{i=1}^{n} E_i\right)^{-1}, \ldots, E_n\left(\sum_{i=1}^{n} E_i\right)^{-1}\right) \tag{4}$$

where $T_i^{"}$ is the normalized feature vector, which carries the information of signal. It can be used to classify signals, so as to assess the performance status.

2.3. Fault diagnosis and MQE calculation by SOM network

In SOM, each neuron is represented by a dimensional weight vector and connected to adjacent neurons by a neighborhood relation, which indicates the topology of the map [3]. During training procedure, take vector X for example, the distance between it and all the weight vectors of SOM is computed by using distance measure. The neuron whose weight vector is closest to X is called Best Matching Unit (BMU) [4]. The weight vector of BMU is enhanced by the learning rule.

After training, the neurons are grouped in clusters by their distance in the structure, which form a new kind of topology. When test vectors input, the vector is compared with the weight vectors of all map units in SOM. Fault mode can be judged by the topological structure of SOM. And, depending on how faraway the current data is deviating from the train data, a quantitative assessment index can be obtained by calculation of the Minimum Quantization Error (MQE) [5]. MQE value is figure out by:

$$MQE = \| X_{input} - w_{bmu} \| \tag{5}$$

where, X_{input} is the input data vector, and w_{bmu} is the weight vector of BMU.

2.4. Feature optimization by Taguchi method

The optimization starts with the normal and faulty feature vector, then the MQE is figure out as preceding part of this text. After that, Taguchi method creates a standard orthogonal array (OA), which depends on the number of factors and levels needed. The optimum experimental conditions can be easily determined with the OA. In the OA, features have two levels. Level-1 represents the presence of a feature, while level-2 represents the absence of a feature. Here, nine MQEs are calculated with the combination of the features dictated by the OA and the larger-the-better signal-to-noise ratio (SNR) is calculated as follows:

$$m_i = -10\log\left[\frac{1}{n}\sum_{j=1}^{n}\frac{1}{MQE_j}\right] \tag{6}$$

where m_i is the SNR for the ith run of the OA, and n is the sample size of each abnormality. Then, an average SNR at level-1 and level-2 of each feature is obtained and the gain is calculated as below [6].

$$Gain = Mean_{level1} - Mean_{level2} \tag{7}$$

According to principle, features with positive gain are selected for the performance assessment and the rest are discarded.

2.5. Performance assessment by CV

In this approach, CV, proposed by Qiu et al. [7], is introduced as an index to evaluate the performance status. The CV can be formulated as below:

$$CV = \exp\left(-\frac{MQE^{1/2}}{c_0}\right) \tag{8}$$

where MQE is just the MQE under the monitoring data offered by SOM running. c_0 is scale parameter determined by the MQE under the normal state and the predetermined CV.

According to the principles of SOM and MQE, normal signals with the similar features to the trained dataset, will gather around the normal cluster, which should have a minimum MQE value relative to that of other faulty status. Along with the operation of pump, features of the signal turn to be different from the trained data, therefore MQEs of them will become higher. CV is inverse proportional to the MQE, so normal pump get higher CV, and faulty ones trend to be lower as well.

2.6. Flow of the proposed method

The aforementioned constitutes performance assessment and fault diagnosis. The process can be summarized as Figure 1.

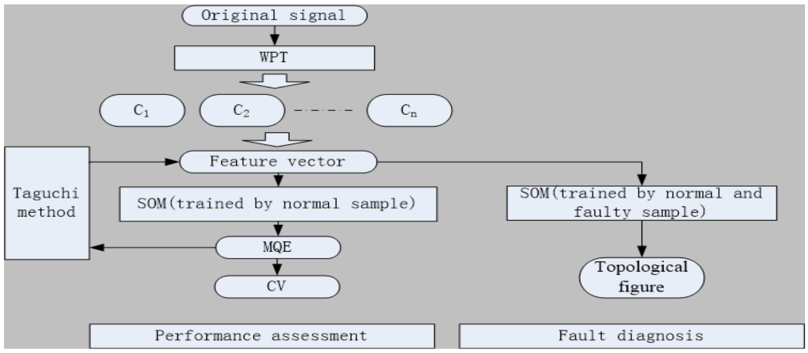

Figure 1. Flow of the proposed method.

3. Experimental Verification

3.1. Experiment setup

In this study, a test plunger pump rig was tested and analyzed to verify the presented method. The vibration signal was acquired from the end face of the plunger pump with a stabilized motor speed of 528r/min, and sampling rate of 1000Hz, as shown in Figure 2. Two commonly occurring faults in the plunger pump were set, namely, swash plate wear and rotor wear.

Figure 2. Test plunger pump rig.

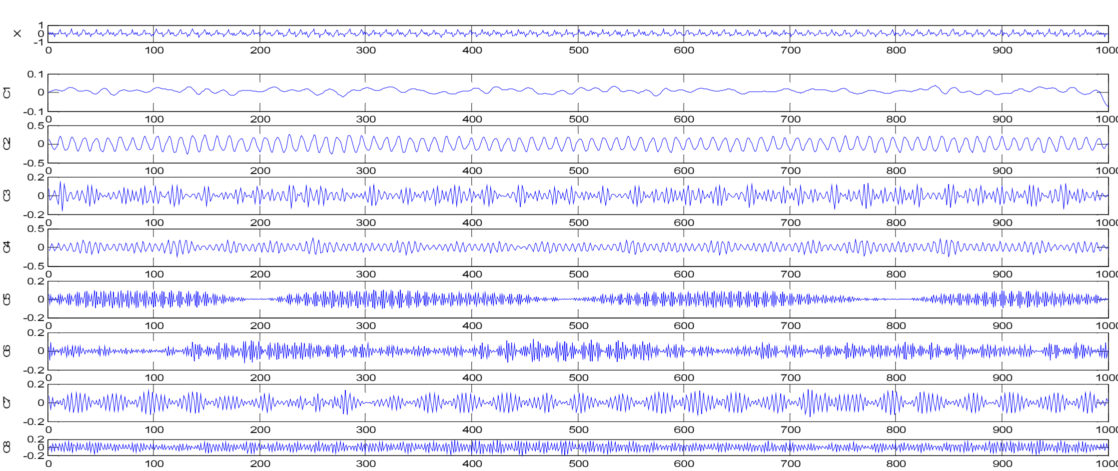

Figure 3. A sample of WPT results of hydraulic pump signal.

3.2. Experiment results and discussion

3.2.1. Feature extraction. Original vibration signal of hydraulic pump is shown in Figure 3. Here, WPT is employed to decompose it into components.

Energy of components is extracted to form feature vector. Table 1 shows 8 groups of normalized feature vectors from the normal samples.

Table 1. Feature vector.

NO.	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8
1	0.3393	2.5319	0.8789	1.6472	1.0084	0.8393	0.8632	1.2736
2	0.3478	2.5081	0.8403	1.6266	0.8638	1.0336	0.8560	1.2394
3	0.3441	2.5544	0.8547	1.6328	1.0271	0.8498	0.8260	1.2399
4	0.2998	2.5475	0.8050	1.6295	0.8677	0.9842	0.8373	1.2632
5	0.2746	2.5443	0.8867	1.6499	0.9887	0.8384	0.8893	1.2999
6	0.3646	2.5096	0.8442	1.5906	0.8659	0.9996	0.8187	1.3576
7	0.3171	2.5314	0.8504	1.5450	0.9480	0.9248	0.8309	1.4178
8	0.3420	2.4554	0.7721	1.5553	0.9031	0.9380	0.7934	1.4749

Table 2. Result of Taguchi method.

Factor / *E*	1	2	3	4	5	6	7	8	m_i
1	1	1	1	1	1	1	1	1	0.54
2	1	1	1	1	1	2	2	2	-3.36
3	1	1	2	2	2	1	1	1	0.02
4	1	2	1	2	2	1	2	2	-4.52
5	1	2	2	1	2	2	1	2	-0.27
6	1	2	2	2	1	2	2	1	-3.29
7	2	1	2	2	1	1	2	2	-0.15
8	2	1	2	1	2	2	2	1	-2.39
9	2	1	1	2	2	2	1	2	-3.39
$Mean_{level1}$	-1.81	-1.45	-2.68	-1.37	-1.56	-1.03	-0.78	-1.28	
$Mean_{level2}$	-1.97	-2.69	-1.22	-2.27	-2.11	-2.54	-2.74	-2.34	
Gain	0.16	1.24	-1.47	0.90	0.55	1.51	1.97	1.06	

3.2.2. SOM-based MQE calculation with Taguchi method. SOM is trained by the vector from normal samples. With the trained SOM, MQE of each vector can be calculated. Then, Taguchi method is introduced in optimization, two samples from normal and faulty pumps, respectively, are sent to Taguchi experiment. The result is shown as Table 2.

According to the rules of Taguchi method, factor-3 with negative gain should be discarded. The rest are selected to constitute final vectors.

3.2.3. Performance assessment. In this experiment, thirty samples from normal and two modes of faulty pump, respectively, are chosen to assess, the MQE and CV curves are shown in Figure 4.

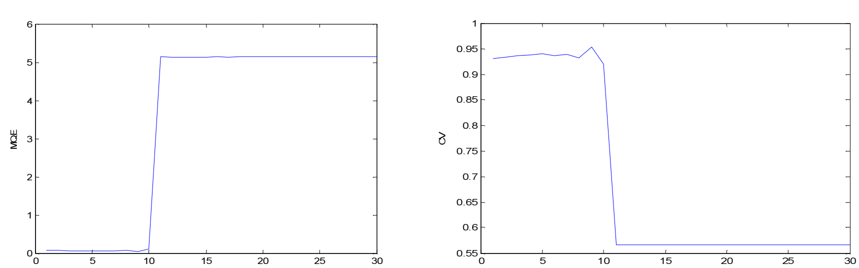

Figure 4. MQE and CV of the hydraulic pump.

The blue curve in the figure shows trend of CV, the first ten samples from normal pump show high CVs above 9.0, which indicates hydraulic pumps are in good state; while, CVs of the last twenty ones from faulty pumps fall down obviously. Thus, it is clear that CV coincidently represents the performance of hydraulic pumps, and it is also distinctly proved that this approach to performance assessment is feasible.

3.2.4. Fault diagnosis. Here, three hundred from normal and two modes of faulty pump, respectively, are chosen to train SOM. With the trained SOM, datasets from three modes of pumps is employed to fault diagnosis, the topological structure and the result is shown in Figure 5.

As is shown in Figure 6, Samples from three modes severally maps in the topological structure which represents normal, rotor wear, swash plate wear. Fault mode of hydraulic pump can be judged directly by the topological figure, which shows the effectiveness of the approach.

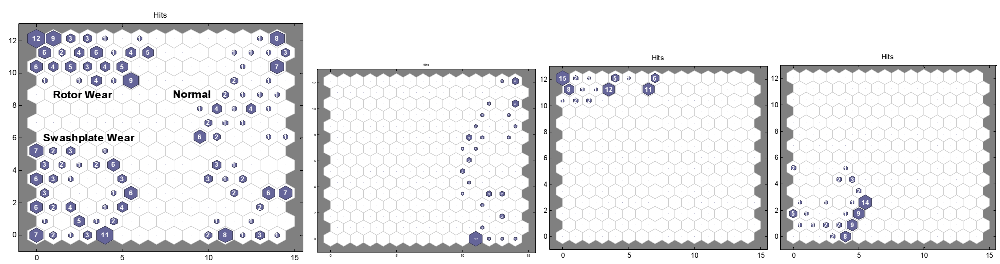

Figure 5. Topological structure of trained SOM and results of fault diagnosis (from left to right, normal, rotor wear, swash plate wear).

4. Conclusions

In this paper, a method for performance assessment and fault diagnosis to hydraulic pump is proposed. WPT is utilized as a powerful signal processing method for nonlinear and non-stationary vibration signal. A SOM based MQE chart is employed to assess performance of hydraulic pump by tracking the trends of CVs. Meanwhile, topological figure of the SOM, trained by both normal and faulty samples, classify the faults into different fault modes. Additionally, the employment of Taguchi method makes the result more accurate, and the optimization of the feature vector reduce computations as well, which is meaningful for real-time assessment.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (Grant Nos. 61074083, 50705005 and 51105019), as well as the Technology Foundation Program of National Defense (Grant No. Z132010B004).

References

[1] Peng X L, Hao H and Li Z X 2012 *Engineering Structures* **39** 50–65
[2] Jafar Z and Javad P 2007 *Tribology International* **40** 763–9
[3] Ai C S, Sun Y J, He G W and Ze X B 2012 *The International Journal of Advanced Manufacturing Technology* **61** 457–63
[4] Pham D T, Dimov S S, Bigot S, Ivanov A and Popov K 2004 *Journal of Materials Processing Technology* **149** 50–7
[5] Yu J B and Wang S J 2009 *Computers & Industrial Engineering* **57** 1300–12
[6] Taguchi G and Jugulum R 2002 The Mahalanobis–Taguchi Strategy: A Pattern Technology System
[7] Qiu H, Lee J, Lin J and Yu G 2003 *Advanced Engineering Informatics* **17** 127–40