Performance Degradation Analysis of Axial Piston Pumps Based on Self-Organizing Map

Xiaokai Huang
Beijing Institute of Spacecraft Environment Engineering
Beijing, China
huangxiaokai511@126.com

Zemin Yao
Beijing Institute of Spacecraft Environment Engineering
Beijing, China
buaayzm@126.com

Shouqing Huang
Beijing Institute of Spacecraft Environment Engineering
Beijing, China
hshouqing@163.com

Dazhi Liu
Beijing Institute of Spacecraft Environment Engineering
Beijing, China
36217918@qq.com

***Abstract*—Axial piston pumps are key components in hydraulic systems, and their real-time performance degradation analysis has received more and more attention in engineering practice. This paper proposes a degradation trajectory method based on self-organizing map (SOM), which is used to analyze the performance degradation of axial piston pumps. Firstly, a self-adaptive Morlet wavelet filter is applied to process the vibration signals of axial piston pumps, and time-domain metrics of filtered signal is used as eigenvectors which can reflect the performance degradation degree. Then data from typical status are used to train SOM, and trajectory on the output layer of SOM is used to represent the real-time performance of degradation degree. Lastly, the performance degradation experiment of axial piston pumps was carried out and the results showed that the proposed method can describe performance degradation process of axial piston pumps effectively.**

Keywords- Axial piston pumps; Performance degradation; Self-adaptive Morlet wavelet filter;Self-organizing map

I. INTRODUCTION

The hydraulic system is widely used in shipbuilding, machine manufacturing and aerospace due to its high power-mass ratio and response speed. Hydraulic pumps, as the power elements of hydraulic system, are capable of converting mechanical energy into hydraulic energy. As the most commonly-used hydraulic pumps, axial piston pumps absorb and discharge oil by changing the volume of sealed chamber, which is conducted through the reciprocation of piston inside the cylinder. Because of its high rated pressure, compact structure, high efficiency and flexible flow regulation, the axial piston pump has been widely used in industries entailing properties above, such as aircraft, engineering machine and shipbuilding. The failure of piston pumps may bring about malfunction of major systems, even leading to the raise of economic losses and casualties. It is of great significance to monitor the real-time status of pumps and guarantee their reliabilities during runtime [1].

Up to now, researches on the reliability of axial piston pumps mainly focus on fault mechanism and diagnostic methods, including tribological behaviors of three friction pairs, compound friction and wear behaviors of dynamic oil-film and fault diagnosis based on return oil flow [2,3,4]. Compared with traditional diagnostic methods, performance degradation analysis can reflect the status and degradation degree of the system in real time, at the same time, provide the choice of proper maintenance policies. Because it can ensure the working time or efficiency of systems, performance degradation analysis has been widely valued [5].At present, performance degradation analysis is mainly achieved by real-time monitoring, and intelligent analysis methods are used to build performance degradation metrics, whose variation tendency serves to assess the degradation degree of actual systems [6,7,8].In this paper, precise performance degradation metrics play an important role for accurate assessments.

Based on the above-mentioned methods, this article proposes a degradation trajectory method based on self-organizing map (SOM) to evaluate the performance degradation of axial piston pumps. According to the working conditions of actual systems, time domain metrics of axial and radial vibration signals are chosen to build the eigenvectors, which also work as the input of SOM. Considering that real-time systems are exposed to strong jamming, self-adaptive Morlet wavelet filter is used to process the original vibration signal and highlight the characteristic information. SOM is favored due to its unsupervised learning scheme and ability to form intuitional clustering results on the output layer. If data from typical status are used to train SOM, clusters that belong to different status can be recognized from the output layer. If each output unit is matched with corresponding input eigenvector and arranged in time sequence, a trajectory reflecting the degradation history of certain sample can be built, then the timeline of degradation also can be ascertained. The remainder of this paper is organized as follows. Section 2 analyzes the fault mechanism of axial piston pumps and expounds how to process vibration signals with self-adaptive Morlet wavelet filter and to get access to eigenvectors. In Section 3, specific steps of performance degradation analysis based on SOM are presented. Section 4 illustrates the implementation processes of degradation experiments for axial piston pumps and the performance degradation analysis is

978-1-7281-0860-5/19/$31.00 ©2019 IEEE

performed with proposed method. Finally, the conclusion is drawn in Section 5.

II. FAULT MECHANISM ANALYSIS AND FAULT FEATURE EXTRACTION

A. Operating principle and failure modes of axial piston pumps

The axial piston pump is composed of key elements including valve plate, cylinder, pistons and swash plate. The schematic of its structure is presented in Figure 1. Driven by motor or other rotating machines, axial piston pumps generate hydraulic power through the reciprocating motion of pistons inside the cylinder. The cylinder (also known as rotor), pistons, valve plate, swash plate, slipper and pump body form the vibration system, which is motivated to vibration when the principal axis rotates at a certain speed. In general, aforementioned vibration during operation can be classified into two types. The first one is the vibration related to the elasticity of components while another one is in connection with surface conditions such as scratch and crack. The former contributes nothing to abnormal operation status, but the latter reflects the damage status of major frictional parts within the pump.

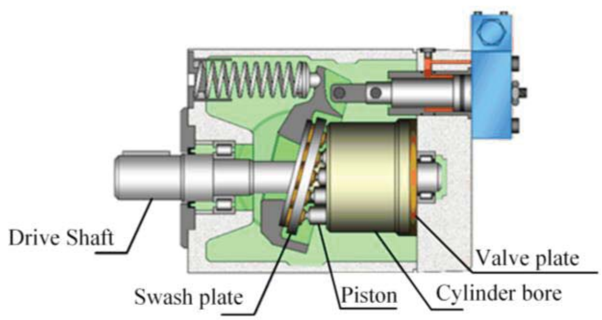

Figure 1. Structure of axial piston pump

Axial piston pumps may suffer four most common faults, which lie in four friction pairs, swash plate/slipper friction pair, valve plate/cylinder block friction pair, and piston/cylinder bore friction pair and bearing respectively. It is widespread to diagnose these faults using vibration signals. When the axial piston pump is in operation, the surface of the friction pair gradually becomes scratched due to abrasion, giving rise to pulses in the vibration signal. Because the friction pairs have diverse structures and materials, the time-domain features of pulse signal differ sharply. However, given the high speed and strong vibration, pulse signals generated by wear of friction pairs are overlapped by other signal components in practice, thus cannot be detected with regular methods.

Wavelet analysis overcomes the defect of single resolution for regular Fourier transformation and can perform more effective detection for the local feature of signal. Among various wavelets, the shape of Morlet wavelet is similar to that of pulse signal, which makes Morlet wavelet widely used in pulse detection.

B. Self-adaptive morlet wavelet filter and failure feature extraction of axial piston pumps

Wavelet transformation is defined as the convolution between signals and the wavelet group. Within the wavelet group exists at least one mother wavelet $\psi(t)$, whose scale can be expanded, retracted and shifted to generate a series of wavelets as follows:

$$\psi_{(a,\tau)}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right) \tag{1}$$

in which a is the dimension parameter while τ is the time parameter.

In the time domain, Morlet wavelet is defined as the product of sine wave and Gaussian function depicted as follows:

$$\psi(t)=ce^{-\sigma^2t^2}e^{i2\pi f_0 t} \tag{2}$$

where σ is the shape parameter, f_0 is the central frequency of wavelet, and c is a positive number usually defined by $c=\sigma/\sqrt{\pi}$, The waveform of Morlet wavelet is presented by Figure 2.

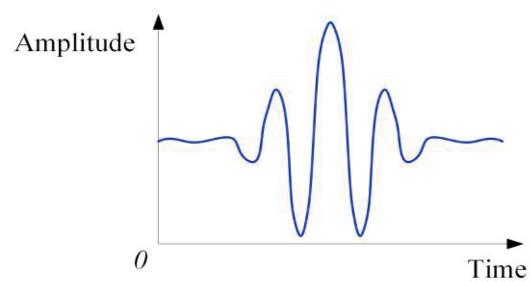

Figure 2. Waveform of Morlet wavelet

The Morlet wavelet filter can be represented by a band-pass filter whose range of passing band is $[f_0-\beta/2, f_0+\beta/2]$.The parameter β can be given as:

$$\beta=\frac{\sqrt{2\ln 2}}{\pi}(\mathrm{Hz}) \tag{3}$$

The output of Morlet wavelet filter is analytic signal $WT(f_0,\beta)$, whose modulus can be calculated to identify the envelope of filtered signal as:

$$S(t)=\sqrt{\left[\mathrm{Re}(WT)\right]^2+\left[\mathrm{Im}(WT)^2\right]} \tag{4}$$

Generally speaking, a Morlet wavelet filter with fixed parameters can be built based on signal frequency f and band width β. However, the vibration performance of axial piston pumps is not constant. On the one hand, the surface appearance of inner damage region is always changing due to friction and wear. On the other hand, as the axial piston pump is composed of enclosure and inner components, the vibration performance of diverse pumps may differ sharply due to machining accuracy and error. Thus, it is crucial to establish a self-adaptive Morlet wavelet filter to adjust the value of f and β in accordance with specific signals. Kurtosis enables to measure the pulse components within the signal so it is widely used in detection.9

In this article, kurtosis is chosen to indicate the performance of Morlet wavelet filter. For each section of original signal, the values off and β maximizing the kurtosis are the desirable parameters of self-adaptive Morlet wavelet filter.

The kurtosis can be defined as follows:

$$Kurt(y) = \frac{1}{N}\sum_{i=0}^{N-1}\left(x_i - \bar{x}\right)^4 / \sigma^4 \tag{5}$$

in which y is the sampling time series, N is the length of y. Considering that sampled signals are all discrete in practice, N is actually the number of sampling points.

The flow chart of parameter determination for self-adaptive Morlet wavelet filter is shown in Figure 3.

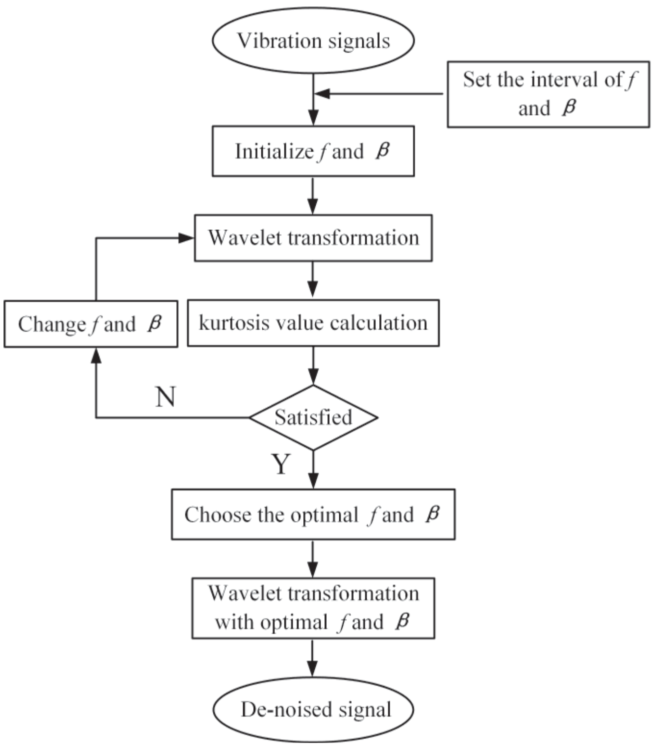

Figure 3. The flow chart of parameter determination for self-adaptive Morlet wavelet filter

Vibration signals processed by self-adaptive Morlet wavelet filter can serve to the extraction of failure feature. In this process, time-domain metrics can be used directly, or frequency-domain and time-frequency-domain metrics can be attained through transformation. In this article, the effective value, crest factor and kurtosis of filtered signal are chosen as characteristic variables. As each axial piston pump under experiment is equipped with two vibration sensors, one in axial direction while another in radial direction, the dimension of eigenvectors is equal to 6.

III. PERFORMANCE DEGRADATION ANALYSIS BASED ON SELF-ORGANIZED MAP

A. *Introduction of Self-organized Map neural network*

Eigenvectors extracted from processed vibration signal are rich in information of real-time performance of axial piston pumps. Nevertheless, it is hard to obtain degradation performance based on eigenvector directly. SOM enables to extract valid information from high-dimensional input vectors and give an accurate mirror for the complex, high-dimensional relation between input vectors and corresponding performance [9,10,11], In this article the performance degradation of axial piston pumps is analyzed based on SOM.

As an unsupervised learning neural network featuring characteristic map and quantification, SOM differs from most neural networks such as BP and RBF, only having the input layer and output layer.12 One typical structure of SOM is given in Figure 4.

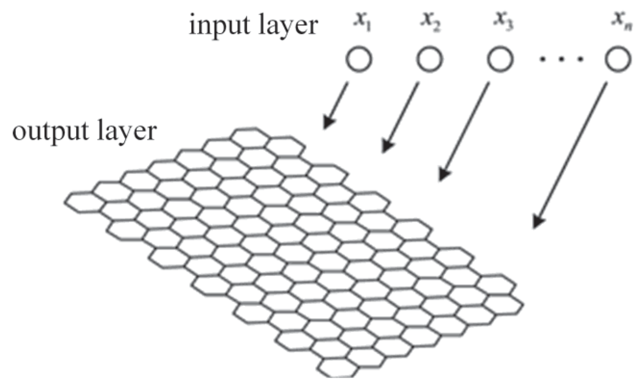

Figure 4. Typical structure of SOM

The number of units on SOM output layer is equal to the dimension of input vector. On the output layer, units usually range themselves into a planar lattice array, within which each rectangular or hexagon lattice is in connection with surrounding ones. The lattice on output layer is also called unit, which is indicated by an n-dimensional weight given by $w_i = [w_{i1}, w_{i2}, \cdots, w_{in}]$, and n equals the dimension of input vector. The weight of each node is corresponding to a position in the input space, and this weight vector has the same dimension as each input vector. In the training process, the weight vectors are updated towards the input data without spoiling the topology of the map space.

The structure of SOM is determined by the number of units on input and output layers, the arrangement of units on output layer and the contiguous relations. All of these need to be ascertained before training, then specific algorithm can be adopted to train the SOM through stepwise iteration. In each step, a vector X must be chosen out of the input vectors to calculate the distances between it and every unit on the output layer in accordance with specific method. The unit nearest to X is dubbed as the best matched unit (BMU). After the determination of BMU, this BMU and surrounding units need to be updated as:

$$\omega_i(t+1) = \omega_i(t) + \alpha(t)h(n_{BMU}, n_i, t)\left(X - \omega_i(t)\right) \tag{6}$$

Where $h(nBMU,n_i,t)$ represents the contiguous relation between units, $\alpha(t)$is the monotone decreasing function of learning efficiency, ranging from 0 to 1. In general, the process of training can be divided into two stages. The first one is called fast learning, in which the training is carried out at a relatively high speed with $\alpha(t)$ approximating 1. The second stage is referred to as fine-tuning adjustment, in which *α(t)* decreases towards 0. When the distance between the BMU and n_i in the grid is smaller than a certain threshold, the training transits into tuning process, i.e. from Stage 1 into Stage 2.

After training, units on the output layer of SOM will form clusters, and the optimum number of clusters can be determined by Davies-Boulding cluster factor[12,13]. Based on given visual observation methods, SOM enables to reflect the fundamental structure of state space and is effective in observing system status and degradation [14,15]. In this article, a degradation trajectory method is proposed to analyze the degradation of performance based on SOM.

B. Degradation trajectory method based on Self-adaptive Map neural network

In accordance with the basic principle and topology of SOM, BMUs belong to contiguous input vectors pertain to the same cluster. If certain abnormal faults such as the drop-dead halt induced by external shocks are left out, most faults are developed progressively the wear and fatigue, for example. On this note, if eigenvectors reflecting the degradation mechanism are extracted throughout entire process of fault, then their BMUs can be integrated into one trajectory tracking the variation from normal status to corresponding fault status. As mentioned previously, axial piston pumps mainly suffer four faults, three friction pairs (swash plate/slipper, valve plate/cylinder block, and piston/cylinder bore) and the bearing respectively. If vibration signals corresponding to these faults and normal status are available, then eigenvectors can be extracted from them to train the SOM. After the training, each status, whether it is normal or abnormal, will form a region mapped with certain cluster on the output layer. If eigenvectors extracted from the degradation experiment are put in time order, a degradation trajectory will shape on the output layer, moving away from normal status to fault status. The time-varying statuses of axial piston pumps can be analyzed based on this trajectory.

The flow chart of degradation trajectory method based on SOM is given in Figure 5.

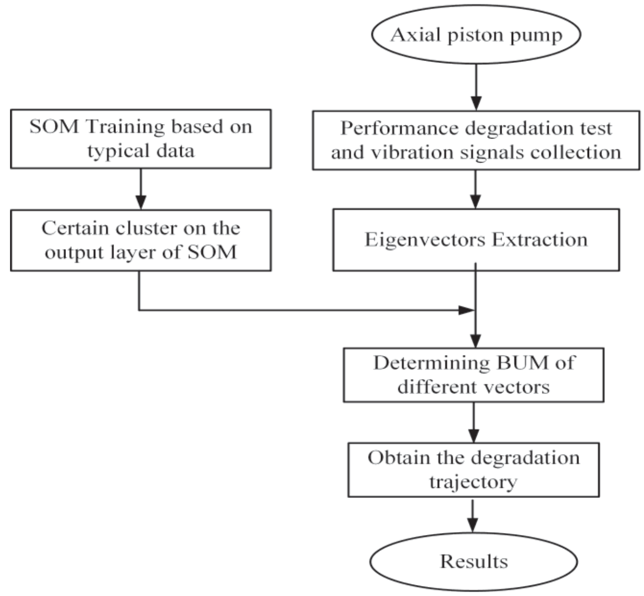

Figure 5. The flow chart of parameter determination for self-adaptive Morlet wavelet filter

IV. PERFORMANCE DEGRADATION EXPERIMENT AND ANALYSIS OF RESULT

A. Experimental facility

Performance degradation experiments of axial piston pumps were carried out to verify proposed method. The structure of test bench is given in Figure 6(a). Axial piston pumps under experiment are of the same type, with rated pressure of 21Mpa, rate speed of 1450rpm and rate flow of 50L/min. The sample size is 4 and stress levels applied are listed in Table 1. Each pump under experiment is fitted with one vibrating sensor in radial direction and the other one in axial direction. The layout of sensors is given in Figure 6(b).

The data acquisition system contains one industrial control computer and one board of Yanhua PCI-1716 model. Inner program is written based on LabWindows CVI of NI and the sampling frequency of vibration signal is 20Hz. During entire process, data were collected for 10 seconds every 2 hours. The experiment continued for 80 days.

B. Preliminary analysis of results

During the experiment the faults of axial piston pumps are judged by operators in accordance with the vibration signal and return oil flow signal. The sensor detecting return oil flow is not marked in Figure 6. In fault status, each axial piston pump was kept operating for another 4 hours to acquire corresponding signals. After the experiments every pump was disassembled and checked, and the observed results confirmed the judgement of operators. As shown in Table 2, at the end of experiments, pump 1 and pump 2 failed due to the excessive wear of swash plate/slipper friction pair and valve plate/cylinder block friction pair respectively. Pump 4 remained functioning, but suffered performance degradation to some degree.

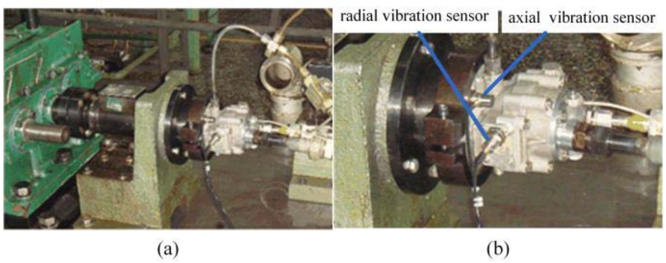

Figure 6. The structure of test bench

TABLE I. STRESS LEVELS OF AXIAL PISTON PUMPS

No.	*Pressure/Mpa (Rad/s)*	*Speed/ rpm (Rad/s)*	*Temperature/℃*
1	21	1500	20
2	21	1000	20
3	14	1500	20
4	14	1000	20

TABLE II. OBSERVED RESULTS OF AXIAL PISTON PUMPS

No.	*Test Results*	*Failure time/d*	*Checked and observed results*
1	failed	21	excessive wear of swash plate/slipper friction pair
2	failed	44	excessive wear of valve plate/cylinder block friction pair
3	failed	77	much wear of three friction pairs
4	censored	-	little wear of three friction pairs

The vibration signals detected by axial sensors on four test pieces are given in Figure 7. It can be seen from Figure 7, the kurtosis values of four pieces approximate 3 during the inceptive stage. For pump 1, this duration is short, followed by the rise of kurtosis with severe oscillation. The inceptive stage of pump 2 endures longer, then the kurtosis value exceeded 3 around 16th day and remained for several days. On Day 33, the kurtosis value started oscillating sharply and dropped to a value approximating 3 in the end. The kurtosis of pump 3 remained relatively stable until Day 30, after that, the value rose and exceeded 3 with slight oscillation. On around Day 64, severer oscillation of kurtosis emerged and remained for a short time, finally dropping to around 3. The stable inceptive stage of pump 4 continued for 48 days roughly, following that the kurtosis went beyond 3 and the oscillation strengthened slightly. At the end of the experiment, the kurtosis value of pump 4 remained at approximately 4.

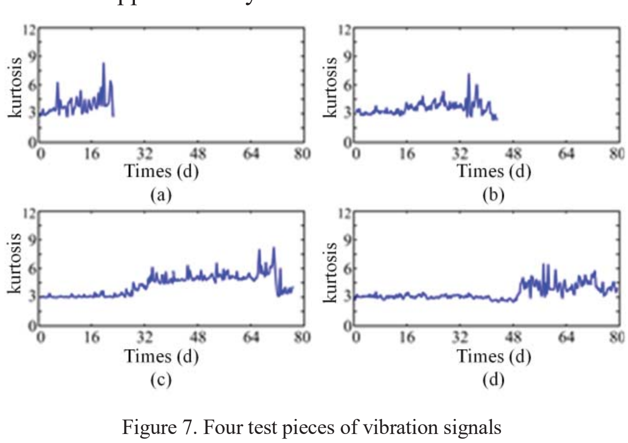

Figure 7. Four test pieces of vibration signals

Based on analysis above, the failure process of axial piston pumps can be broken into different stages with respect to the kurtosis value. Nonetheless, because of the precise timeline of failure cannot be determined, it is difficult to meet the requirements for accurate performance degradation assessment.

C. Performance degradation analysis of axial piston pumps based on degradation trajectory method

In this paper, the SOM tool kit developed by Helsinki University of Technology is adopted in relevant calculation. After the degradation experiments, axial and radial vibration signals of each sample were filtered by self-adaptive Morlet wavelet filter. The effective value, crest factor and kurtosis value of filtered signals were computed to build eigenvectors. On this note, the dimension of SOM input vector is equal to 6, while the number of units and the length-width ratio of SOM output layer is identified by SOM tool kit automatically.

As mentioned previously, typical faults of axial piston pumps include those on three friction pairs, and faults of bearings. Because life tests for this type of pump had been carried out before, the axial and radial vibration data collected in normal and fault status -including degradation and fault status- were used to train the SOM directly. The results of training are shown in Figure 8.

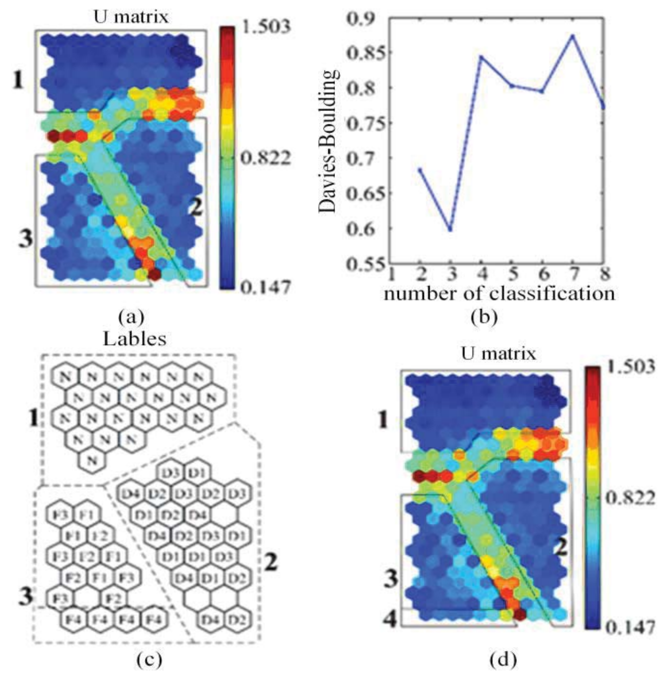

Figure 8. The results of SOM training

The *U* matrix of SOM can be used to measure the distance between each unit on the output layer with surrounding units, thus it is frequently used to show the results of classification. The *U* matrix of SOM obtained after training is given in Figure 8(a). With respect to color, the number of groups is roughly estimated as 3. The Davies-Boulding clustering coefficient curve shown in Figure 8(b) confirms the number of optimal classification to be 3. The labeled output layer of SOM is shown in Figure 8(c), in which N represents normal statuses, while D_1, D_2, D_3 *and* D_4 represent degradation statuses owing to the malfunction of rotor-port plate friction pair, piston-cylinder friction pair, piston shoes-swash plate friction pair and the bearing respectively. Alongside that, F_1, F_2, F_3 and F_4 represent corresponding fault statuses. As shown in Figure 8(c), normal statuses form an independent class, namely Class 1. Four degradation statuses are mixed together, thus they can be assorted to Class 2. F_1, F_2 and F_3 are mixed with each other, yet separated from F_4, so F_1, F_2 and F_3 are assorted to Class 3, while F_4 is listed as Class 4. The final classification is given in Figure 8(d).

Figure 9 presents the degradation trajectories of four test specimens. For pump 1 and pump 2, each single point represents one status continuing for two days, while for pump 3 and pump 4, each point represents a status enduring five days. As shown in Figure 9, pump 1 turn to class after 20 days, and pump failed after 40 days. Same as pump 3, the failure time point is the 75th day, the pump 4 still work in class 2. Compare with Table 2, time-points of degradation and fault stages can be given by the degradation trajectory of each test specimen. Estimated time-points of fault statuses roughly conform with the observation of operators.

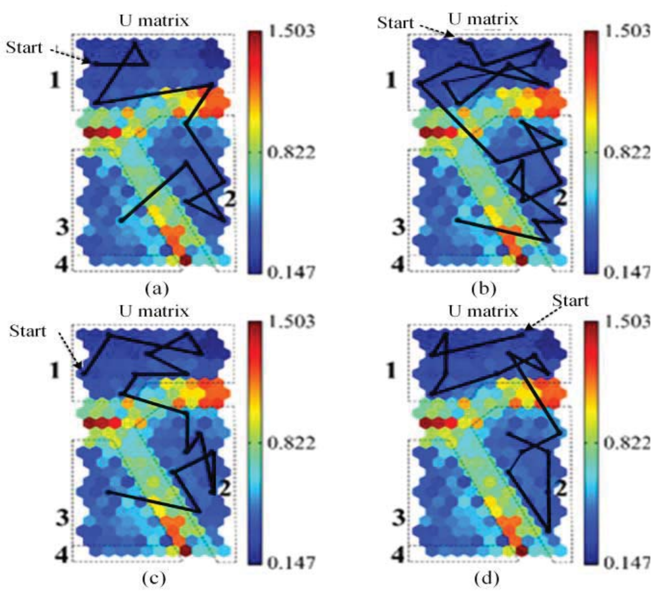

Figure 9. Degradation trajectories of four test specimens

V. CONCLUSION

In this paper, a degradation trajectory method based on SOM is presented to analyze the performance degradation of axial piston pumps. Firstly, self-adaptive Morlet wavelet filter is built to filter axial and radial vibration signals and the time-domain metrics extracted from processed signals serve as eigenvectors mirroring performance degradation. Then, data of typical statuses are used to train the SOM. Contraposing each eigenvector, corresponding BMU on the output layer is calculated. The trajectory of BMU reflects the real-time degradation degree of axial piston pumps. Alongside that, experiment was carried out and the results verified that the proposed method can provide assessment for performance degradation with better accuracy. Further research may be focused on building more intuitive and effective metrics based on SOM to reflect the degree of performance degradation.

ACKNOWLEDGMENT

This work was supported by the Equipment Pre- research Project (41402010201).

REFERENCES

[1] Zhao Z, Jia M, Wang F, Wang S, "Intermittent chaos and sliding window symbol sequence statistics-based early fault diagnosis for hydraulic pump on hydraulic tube tester," Mechanical Systems and Signal Processing. vol. 5 pp:1573–1585, February 2009.

[2] Gao Y, Zhang Q, Kong X, "Wavelet-based pressure analysis for hydraulic pump health diagnosis," Transactions of the ASAE. Vol 4 pp:969–976, March 2003.

[3] Gao Y, Zhang Q, "A wavelet packet and residual analysis based method for hydraulic pump health diagnosis," Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering. Vol 6 pp:735–745,April 2006.

[4] Chen H X, Chua P S K, Lim G H, "Fault degradation assessment of water hydraulic motor by impulse vibration signal with wavelet packet analysis and KolmogorovSmirnov test," Mechanical Systems and Signal Processing. Vol 7 pp:1670–1684, May 2008.

[5] Lee J, "Measurement of machine performance degradation using a neural network model," Computers in Industry. Vol 3 pp:193–209, June 1996.

[6] Huang R, Xi L, Li X, Liu CR, Qiu H, Lee J, "Residual life predictions for ball bearings based on self-organizing map and back propagation neural network methods," Mechanical Systems and Signal Processing. Vol 21:193–207, July 2007.

[7] Ocak H, Loparo K. A., Discenzo F. M., "Online tracking of bearing wear using wavelet packet decomposition and probabilistic modeling: A method for bearing prognostics," Journal of sound and vibration. Vol 302 pp:951–961, August 2007.

[8] Pan Y, Chen J, Guo L, "Robust bearing performance degradation assessment method based on improved wavelet packetsupport vector data description," Mechanical Systems and Signal Processing. Vol 23 pp:669–681.September 2009.

[9] Lin J, Zuo M J, "Gearbox fault diagnosis using adaptive wavelet filter, "Mechanical Systems and Signal Processing. Vol 17 pp:1259–1268, October 2003.

[10] Sahoo A. K., Zuo M. J., Tiwari M. K., "A data clustering algorithm for stratified data partitioning in artificial neural network," Expert Systems with Applications. Vol 39 pp:7004– 7014. November, 2012.

[11] Tian Z G, Zuo M J, Tiwari M. K., "Health Condition Prediction of Gears Using a Recurrent Neural Network Approach," IEEE Transactions on Reliability. Vol 59 pp:700– 705. December 2010.

[12] Kohonen T., Self-Organizing Maps, Springer, Berlin Heidelberg, 1995.

[13] Wang L, Jiang M, Lu Y, Sun M, Noe F, "A comparative study of clustering methods for molecular data," International Journal of Neural Systems. Vol 17 pp:447–458, April 2007.

[14] Chattopadhyay M., Dan P. K., Mazumdar S., "Application of visual clustering properties of self organizing map in machine-part cell formation," Applied soft computing. Vol 12 pp:600–610, May 2012.

[15] Qiu H, Lee J, Lin J, Yu G, "Robust performance degradation assessment methods for enhanced rolling element bearing prognostics," Advanced Engineering Informatics. Vol 17 pp:127–140, 2003.