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Te HAN
Dongxiang JIANG

FAULT DIAGNOSIS OF MULTISTAGE CENTRIFUGAL PUMP UNIT USING NON-LOCAL MEANS-BASED VIBRATION SIGNAL DENOISING

DIAGNOZOWANIE USZKODZEŃ WIELOSTOPNIOWEJ POMPY ODŚRODKOWEJ Z WYKORZYSTANIEM METODY ODSZUMIANIA SYGNAŁU DRGAŃ W OPARCIU O ŚREDNIE NIELOKALNE

In real industry environment, the signal characteristics of multistage centrifugal pump vibration signal are easily submerged by strong background noise. To settle this problem, the nonlocal means (NLM) approach is proposed for the denoising of multistage centrifugal pump in this paper. Utilizing the similarity theory, the NLM method has achieved a wide range of applications in the fields of image processing and biomedical signal denoising. Due to the periodic characteristics and redundancy, NLM is successfully applied to the de-noising of 1-D machinery vibration signal. The numerical simulation experiments with different SNRs verify the effectiveness and the superiority of the proposed method. Besides, the selection principles of core parameters in NLM are discussed. The real engineering cases analysis demonstrates that the NLM can effectively filter out the background noise and realize the weak fault feature enhancements. The proposed noise reduction method is superior to traditional wavelet coefficient method.

Keywords: *vibration signal denoising, multistage centrifugal pump, nonlocal means, diagnosis.*

W rzeczywistym środowisku przemysłowym, charakterystyki sygnału drgań wielostopniowej pompy odśrodkowej są zagłuszane przez silny szum tła. Problem ten można rozwiązać stosując zaproponowane w niniejszej pracy podejście oparte na algorytmie średnich nielokalnych (non-local means, NLM). Wykorzystująca teorię podobieństwa metoda NLM znajduje szeroki zakres zastosowań w dziedzinie przetwarzania obrazu i odszumiania sygnałów biomedycznych. Dzięki okresowemu charakterowi i redundancji sygnałów, NLM można z powodzeniem stosować do usuwania szumu jednowymiarowego sygnału drgań maszyn. Skuteczność proponowanej metody i jej przewagę nad stosowanymi dotychczas rozwiązaniami zweryfikowano na podstawie eksperymentów symulacyjnych z uwzględnieniem różnych stosunków sygnału do szumu (SNR). Ponadto omówiono zasady wyboru podstawowych parametrów NLM. Analiza przypadków inżynierskich pokazuje, że NLM pozwala skutecznie odfiltrowywać szumy tła i wzmacniać słabe symptomy akustyczne uszkodzenia. Proponowana metoda redukcji szumów przewyższa tradycyjną metodę współczynnika falkowego.

Słowa kluczowe: *odszumianie sygnału drgań, wielostopniowa pompa odśrodkowa, średnie nielokalne, diagnozowanie.*

1. Introduction

Multistage centrifugal pump units are widely used in diverse areas, such as condensate water supply for nuclear power plants, drainage of submarine, agricultural irrigation, etc [7]. The condition monitoring and fault diagnosis technologies are significantly important to improve the reliability and stability during the operation of pump units [4, 9, 12, 13, 26]. Nowadays, vibration signal-based analysis is one of the most efficient methods for condition monitoring and fault diagnosis [6, 17, 19]. However, due to the interference of background noise, the obtained signals often cannot accurately reflect the running state of the pump units. The early fault characteristics are easily submerged by noise, lead to the inexact assessment of health conditions. Consequently, fast and effective noise reduction method is of great significance to accurately extract fault features in the condition monitoring and fault diagnosis of pump units [1, 8].

Because of the complex structure of the multistage centrifugal pump, multiple internal excitation sources, the vibration signal is characterized by strong non-linearity and non-stationarity [1]. Traditional Fourier transform-based denoising methods and FIR filtering methods can't process the non-stationary signal well. Most of current researches about vibration signal denoising focus on some popular techniques, mainly including wavelet analysis, empirical mode decomposition (EMD), singular value decomposition (SVD), etc. Wavelet transform methods have the capability of analyzing non-stationary signals [5, 29]. By scaling and shifting the wavelet basis functions, the local features of signal in time-frequency domain can be appropriately extracted. The wavelet thresholding-based denoising methods have been widely used in noised reduction and diagnosis of mechanical signals. The popular threshold selection methods mainly include uniform threshold, unbiased estimation threshold, minimax threshold, heuristic threshold, etc. Yang et al. proposed an improved wavelet adjacent coefficient-based denoising method by setting the adjacent wavelet coefficient as the whole threshold value, so that filtering the noise and efficiently retaining the impact characteristics in the raw signal [24]. Wu et al. used the threshold estimation method for overlapping blocks to improve the effect of noise reduction [23]. Because of the complexity of mechanical signals, wavelet analysis methods need to set wavelet basis according to signal characteristics in advance. At the same time, the number of decomposition layers has a great influence on the effect of noise reduction. EMD based denoising methods are another branch with no need to set predefined basis function. By decomposing the original signal into a series of Intrinsic Mode functions (IMFs) from high frequency to low frequency, the IMFs that contain the main information can be selected and reconstructed, the high frequency noise in other IMFs can be filtering. Zhang et al. utilized the EMD to decompose the current signal and extract blade imbalance fault feature, which is concealed by the supply frequency and the environment noise [14]. However, end effects, modal aliasing and the selection criteria of IMFs are still the challenges in this branch [1, 10]. The scholars have proposed a series of improved algorithms to overcome these drawbacks, such as ensemble empirical mode decomposition (EEMD) [10], local mean decomposition (LMD) [29] and variational mode decomposition (VMD) [11], while increased the complexity of denoising procedure. In addition, by discarding the high frequency components that represent noise, useful high frequency information is also discarded. The signal processing for each IMFs in such approached is therefore another difficulty. SVD based denoising mainly reconstruct the original signal into a Hankel matrix, and then the matrix is transformed into a factorization form, where diagonal entries are known as the singular values. Each singular value can be reconstructed into a signal components. Generally, the large values of front singular value represent the useful information of raw signal, while the small values of the last ones are related to random noise [20]. The works about the methods to select effective singular values have been often reported [11, 18, 20].

Overall, these aforementioned methods are all based on the idea of decomposition, which may suffer from two difficulties in practical engineering. (1) The selection of predefined basis function and parameter design largely rely on priori knowledge and expert experience. (2) After decomposition, much efforts are need to select and process the useful components while discard the components containing noise. It is highly desirable to investigate the vibration signal denoising methods with easy implementation and simple parameter determination. Non-local mean (NLM) algorithm is a denoising method proposed by Buades et al. in the field of image processing by taking advantage of similar structure characteristics of image blocks [2]. Different from the idea of signal decomposition, the non-local mean algorithm searches for similar structures in the region, and then removes noise by weighted average. Due to its excellent noise reduction ability and relatively simple parameter selection, this algorithm has been successfully applied in image processing, denoising of biomedical signals and other fields [15, 21, 25, 28]. For rotating machinery, vibration signals are usually periodic and cyclo-stationary, and the signal mode reflecting the characteristics of equipment state appears repeatedly with abundant redundant information. These characteristics provide the foundation for the application of this algorithm in denoising of 1-dimensional mechanical vibration signal [27]. This work applied the NLM methods to the denoising of vibration signal of multistage centrifugal pump. The validity and superiority of the method are verified by simulation experiment and analysis of vibration data in real pump unit, providing a fast and effective denoising method for practical engineering.

2. The principle of NLM filtering

NLM filtering focuses on denoising in each region. The core idea is to search similar signal blocks in a neighborhood class and conduct weighted average so as to remove noise and large amount of redundant information in the raw signal. For the vibration signals of rotating machinery, some signal characteristic modes, such as pulse characteristics and periodically appeared rotating frequency components, generally exist. While the noise superimposed on the signal block is random distribution, which can be effectively filtered by weighted average. The core problem of non-local mean denoising is to recover the original signal from a signal containing additive noise. The signal model with additive noise is as follows:

$$v = u + n \tag{1}$$

where v is the measured signal, u is the theoretically noiseless signal and n is the additive white gaussian noise. Given a measured sample s, $\hat{u}(s)$ represents the estimation of the original noise-free signal and it can be calculated by searching a series of similar signal blocks in a neighborhood and making weighted averages. The formula can be described as follows:

$$\hat{u}(s) = \frac{1}{Z(s)} \sum_{t \in N(s)} w(s,t) v(t) \tag{2}$$

where $w(s,t)$ represents the weight of similarity between the t-center signal block and the s-center target signal block, $N(s)$ means the searching neighborhood centered on the target signal block, $Z(s) = \sum_t w(s,t)$ is a normalization constant to represent the sum of the weights of all similar blocks. The weight $w(s,t)$ is calculated as:

$$w(s,t) = \exp\left(-\frac{\sum_{\delta \in \Delta} \left(v(s+\delta) - v(t+\delta) \right)^2}{2 L_\Delta \lambda^2} \right) \tag{3}$$

where λ the parameter of filter, L_Δ represents the data points for signal blocks. The similarity is estimated by the Euclidean distance between the t-center signal block and the s-center target signal block. In Eq (3), the weight of each signal block itself $w(s,s) = 1$. In the field of image processing, to obtain better smoothing effect, the formula for calculating the similarity weight of the central signal block is as follows:

$$w(s,s) = \max_{t \in N(s),\ t \neq s} w(s,t) \tag{4}$$

Considering the non-stationary characteristics of mechanical signals, there is still a large difference in amplitude between the signal blocks with similar structures, which may lead to a low similarity weight and further smooth the original signal. Excessive smooth can result in the loss of signal detail. Therefore, the similar weight correction of the central signal block is not adopted in this work.

It can be seen that the weight depends on the similarity between the signal blocks, rather than only considering the center distance between the signal blocks, so that the weighted average denoising can retain the signal details to the maximum extent. When the search neighborhood covers the whole signal, the algorithm realizes the true non-local mean. However, computational burden increases linearly with the signal length. For one dimensional signal with N data points and search radius with M data points, the computational complexity is $O(L_\Delta NM)$. In this work, the fast non-local mean method proposed by Darbon et al. is adopted for subsequent research [3]. This method can accelerate the calculation process of similar weights by reducing nested cycles, and the computational complexity after optimization is $O(2NM)$. Fig. 1 gives the illustration of NLM parameters. The red patch with center s means the target signal patch, while the yellow patch with center t represents the searched patch in a neighbourhood. The searching region for the neighbourhood contains 2M points with the center of s.

Essentially, different from signal decomposition in most of methods, such as wavelet and EMD, NLM is based on the idea of statistical neighbourhood filter. In contrast to the methods, such as wavelets and Fourier transform, which require predefined basis function, NLM reduces the noise in the raw signal by approximating the signal patch with the self-similar patches in the original signal, instead of decomposition with basis function. Moreover, NLM avoids to identify which decomposed components represent dominantly noise and which components contain primarily main information in the methods, such as EMD and SVD. Consequently, the basic principle of NLM filtering shows the application prospect for vibration signal denoising.

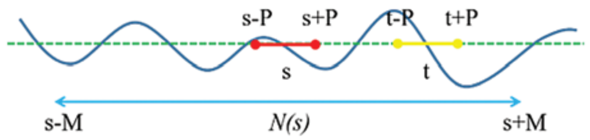

Fig. 1. Illustration of NLM parameters.

3. Parameters criteria

The length of signal block (2P+1) is an important parameter in NLM denoising. When the value of P is too small, the signal block cannot reflect the typical characteristic mode of the signal. At the same time, it is seriously disturbed by noise. When the P is set to a large value, the signal block contains too much information, which is easy to cause smoothing effect in the weighted evaluation process. For the one-dimensional mechanical vibration signal, an appropriate P is usually half of the typical characteristic length, and the specific typical signal block length needs to be selected according to the characteristics of the signal.

For the search radius M of the neighborhood, theoretically, a larger M is benefit to find more similar signal blocks, and more redundant information will be enriched to achieve better noise reduction effect, however, it will bring significant increase in the amount of calculation.

The filter bandwidth λ primary control the smoothing effect in denoising process. A too small λ is likely to cause noise disturbance and affect the size of the weight between the signal blocks, causing an inadequate average. A too large λ will cause a large similarity weight between low-similarity signal blocks, resulting in excessive smoothness and loss of local detail characteristics of the signal. In the field of image processing, according to the SURE criteria of Ville and Kocher [22], $\lambda = 0.5\sigma$, where σ is the standard deviation of noise. Referring to the application of NLM in one-dimensional signal denoising [21], λ is set to 0.6σ in this work. For the real signal, the noise variance can be estimated based on wavelet coefficient.

4. Numerical analysis

Due to mechanical and water flow excitation, vibration signal of multistage centrifugal pump is mainly composed of rotating frequency and its harmonic frequency components. For bearing faults, the signal has obvious impact characteristics. To verify the effectiveness of the method, two sets of simulation signals are designed and analyzed. The noise reduction effect is quantitatively evaluated by introducing three indexes of SNR improvement, mean square error (MSE) and distortion rate (DR). The calculation formulas are as follows:

$$SNR_{imp} = 10\log_{10}\frac{\sum_{n=1}^{N}\left(v[n]-u[n]\right)^2}{\sum_{n=1}^{N}\left(\hat{u}[n]-u[n]\right)^2} \tag{5}$$

$$MSE = \frac{1}{N}\sum_{n=1}^{N}\left(\hat{u}[n]-u[n]\right)^2 \tag{6}$$

$$DR = 100\sqrt{\frac{\sum_{n=1}^{N}\left(\hat{u}[n]-u[n]\right)^2}{\sum_{n=1}^{N}u^2[n]}} \tag{7}$$

where N means the length of signal and the other symbols are same as stated above. The first set of simulation signals is designed as follows:

$$x(t) = \sum_{i=1}^{6} A_i sin 2\pi f_i t \tag{8}$$

where $A_1 - A_6$ are set to 20, 4.5, 2.55, 1.5, 0.4, and 0.3 respectively, $f_1 - f_6$ are set to 20, 2×20, 3×20, 4×20, 0.2×20, 0.3×20 respectively, the sampling frequency is 1000Hz and signal length is 2048 points. The white gaussian noise is added and the SNR is 8dB. The time-domain waveforms of the simulated signal and the noisy signal are shown in Fig. 2:

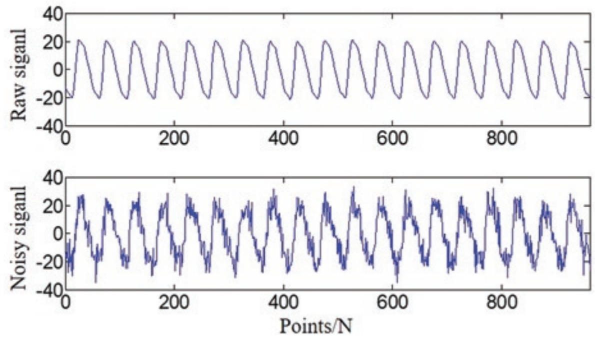

Fig. 2. Time waveform of simulation signal 1

NLM and wavelet soft threshold method (Wden) are used for noise reduction and comparison. The detailed parameters of the two methods are set as follows. NLM: p=30, M=1000, λ=0.6σ. Wden: db10 is selected as wavelet base function, decomposition layer is 5, heuristic threshold criterion is used. The denoising signals are shown in Fig. 3. It can be seen that the NLM algorithm performs better in filtering noise and reflecting the characteristics of the original waveform. The wavelet threshold denoising can obtain smoother original waveform. However, the wavelet basis structure needs to meet the orthogonal premise, while the wavelet basis function insufficiently matches the original waveform features, resulting in the phenomenon of local distortion in denoising signal. Furthermore, the above three indicators are used to conduct quantitative evaluation on the noise reduction performance under different SNR conditions, as listed in Table 1.

The second group of simulation signals are periodic shock signals, and the calculation formula is as follows:

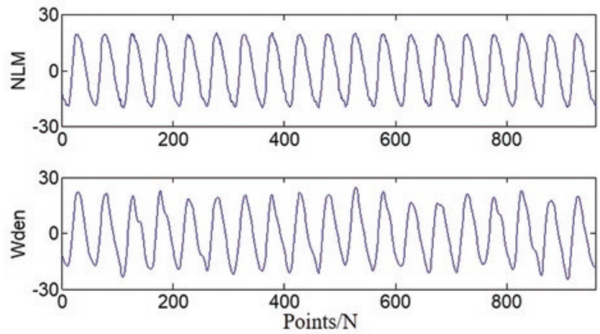

Fig. 3. The comparison of denoising results of two methods for simulation signal 1

Table 1. The denoising results of two methods with different SNRs for simulation signal 1

SNR/dB	NLM			Wden		
	SNR_{imp}	MSE	$DR/10^3$	SNR_{imp}	MSE	$DR/10^3$
8	13.33	1.58	0.47	7.34	6.26	1.43
7	13.73	1.75	0.59	7.48	7.39	1.71
6	11.76	3.58	0.60	8.33	7.88	1.79
5	12.62	3.70	0.75	7.42	12.25	2.26
4	12.43	4.85	0.98	8.36	12.40	2.46
3	10.15	10.22	1.90	7.21	20.09	3.24

$$x(t) = \exp^{-at} \sin(2\pi \times f_c nT)$$
$$t = mod\left(nT, \frac{1}{f_m}\right) \tag{9}$$

where $a = 150$, carrier frequency $f_c = 1000$, fault characteristic frequency $f_m = 20$, sampling frequency is 2500Hz and signal length is 2048 points. The SNR of the noise signal is 4dB, and the time-domain waveform is shown in Fig. 4. Using the same parameter settings above, the results of the two denoising methods are shown in Fig. 5. Under different SNR conditions, the quantitative evaluation results of noise reduction are given in Table 2. Similar conclusions can be drawn that NLM denoising not only enhances the shock characteristics of the signal, but also better guarantees the waveform characteristics of the original impulses. However, the classical wavelet threshold method has obvious distortion. NLM noise reduction signal has a higher reduction degree, compared to the original signal.

Combined with the second set of simulation signal, two key parameters P and M in the NLM denoising process reduction are discussed to provide a clearer guiding principle for the parameter selection in the practical tasks. The curves of SNR enhancement and MSE along with parameters are shown in Fig. 6. Since the result of DR is similar to that of the MSE, it is not shown here. It can be seen that a best noise reduction effect is achieved, when parameter P is set between 30 and 50 points. In the simulation signals, each impulse feature lasts for about 100 points. When P is between 30-50, the signal block with length (2P+1) just reflects the shock feature of the original signal, and thus achieves a good noise reduction effect. At the same time, with the increase of M length in the search neighborhood, the denoising effect is also improved correspondingly. When M contains enough points (M > 2048), the lifting speed of each index gradually slows down.

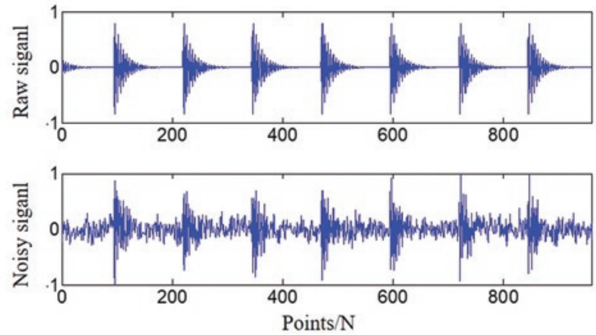

Fig. 4. Time waveform of simulation signal 2

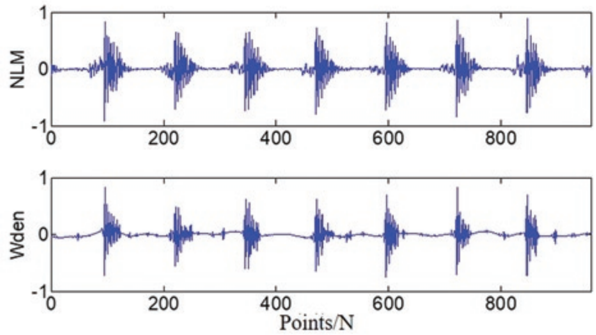

Fig. 5. The comparison of denoising results of simulation signal 2 for two methods

Table 2. The denoising results of two methods with different SNRs for simulation signal 2

SNR/dB	NLM			Wden		
	SNR_{imp}	MSE/ 10^{-3}	DR	SNR_{imp}	MSE/ 10^{-3}	DR
8	10.3	0.51	13.56	2.46	3.1	65.75
7	9.97	0.68	17.25	2.91	3.5	80.62
6	9.73	0.91	23.13	3.40	3.9	99.32
5	8.50	1.5	30.73	3.35	5.0	105.6
4	8.19	2.1	60.96	3.68	5.9	151.7
3	5.93	4.4	103.8	4.02	6.8	157.7

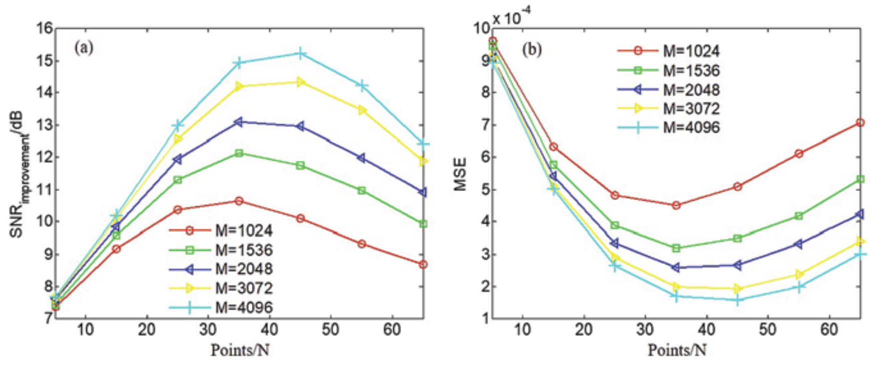

Fig. 6. The improvement of evaluation indicators versus P and M($\lambda = 0.6\sigma$): (a) SNR improvement, (b) MSE

5. Case studies on vibration signal of multistage centrifugal pumps

In order to verify the effectiveness of NLM method in actual industrial tasks, this paper selects two cases of practical vibration fault diagnosis of multistage centrifugal pump sets for analysis. The first analysis case is that the misalignment fault of the motor and the centrifugal pump coupling leads to the excessively high vibration index. The rotating speed of the centrifugal pump is 1490r/min. Vibration signals are collected through the acceleration sensor located at the pump driving end with a sampling frequency of 1280Hz. Time-domain waveforms are shown in Fig. 7, which are further used for denoising (containing 1792 data points). It can be intuitively seen that the vibration signal contains very obvious rotating frequency component. At the same time, some high-frequency components are superimposed on the rotating frequency signal, which interferes with the further identification of faults. NLM is used for denoising. The parameters settings are p=10, M=1024, $\lambda=0.6\sigma$, the noise variance can be estimated from the high-frequency coefficient of the first layer in wavelet decomposition. wavelet soft threshold denoising method is also used for comparative analysis. Wavelet basis function is db10, which highly resembles the vibration signal no matter for the main frequency component or the impulses with high frequencies. In addition, db10 wavelet has orthogonal property which enables perfect reconstruction of signal and have been reported to produce best result according to related works [16]. The number of decomposition layer is 5, heuristic threshold criterion is used.

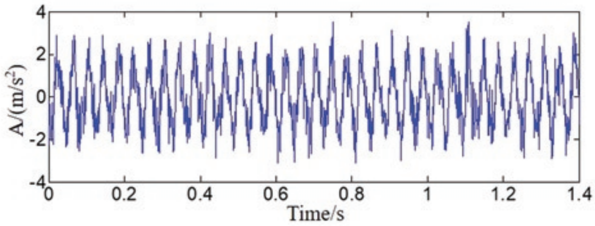

Fig. 7. The vibration signal of multistage centrifugal pump with misalignment

The denoising signals are shown in Fig. 8. From the NLM denoising results, it can be seen that the high frequency noise is effectively filtered. There are obvious harmonic frequency components in the signal. But strong noise interference still exists in the denoising signal for the wavelet threshold method. For practical engineering tasks, the selection of wavelet threshold has a great influence on the result of noise reduction.

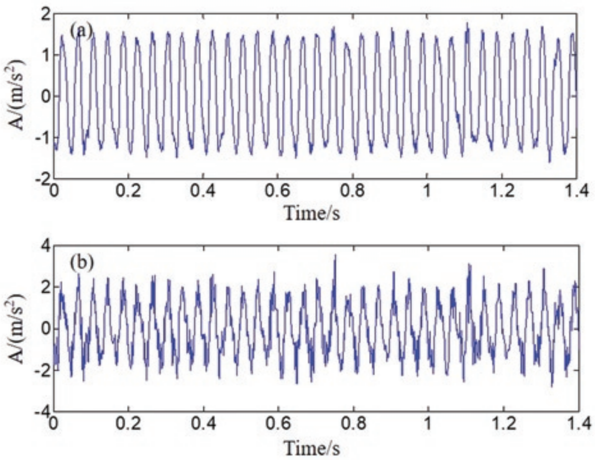

Fig. 8. The denoising results of for two methods in case study 1: (a) NLM, (b) Wden

The fault characteristics can be preliminarily detected from the harmonic frequency. To remove the main frequency component, namely the rotating frequency, and present a clear fault symptom, the ensemble empirical mode decomposition (EEMD) is further utilized to decompose denoising signal and extract the components with fault information for spectrum analysis. The results are shown in Fig. 9 The 1X, 2X and 3X frequency components can be accurately extracted from the spectrum of NLM method. The preliminary judgment is that the coupling alignment occurs. In the wavelet threshold noise reduction method, due to the interference of residual noise, the harmonic frequency components in the spectrum are not obvious.

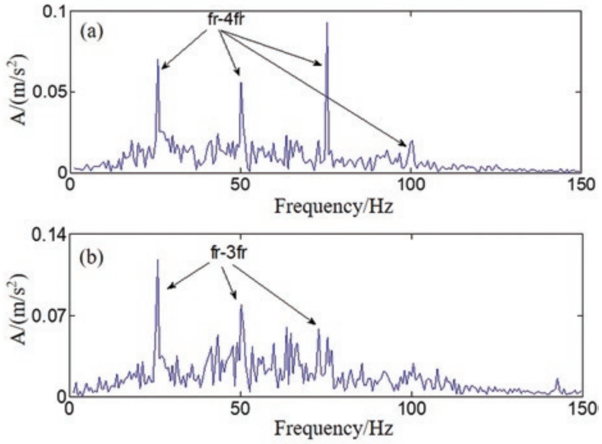

Fig. 9. The frequency spectra of fault component: (a) NLM and (b) Wden

The second case is a bearing fault vibration signal analysis in centrifugal pump. The faults occurs in the outer ring of non-driving end conical roller bearing, resulting in high vibration index. The rotating speed of the centrifugal pump is 1490r/min, and the fault characteristic frequency of the bearing outer ring is $f_o = 236.67$ Hz. The sampling frequency is 1280 Hz. The vibration waveform collected by the acceleration sensor at the non-driving end is shown in Fig. 10.

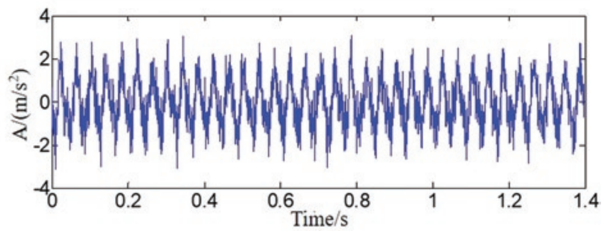

Fig. 10. The vibration signal of multistage centrifugal pump with bearing fault

Similar to case 1, the rotating frequency component in the signal can be clearly found, and at the same time, there are a large number of high-frequency components in the signal. NLM and wavelet threshold are used for denoising respectively. The parameter settings are the same as above. The results of NLM are shown in Fig. 11. A large number of high-frequency components are effectively filtered out, but some high-frequency impulse components still exist in the waveform after denoising. The local amplification of the denoising signal shows that these high-frequency components show obvious characteristics of periodic shock. The preliminary judgment is related to bearing failure. After the envelope analysis of the denoising signal, as shown in the Fig. 11(c), the double fault characteristic frequency $f_o = 473.3$ Hz can be exactly detected. Owing to the weighted average between similar signal blocks, it can be seen that NLM method can effectively filter out noise and enhance the periodicity similar signal

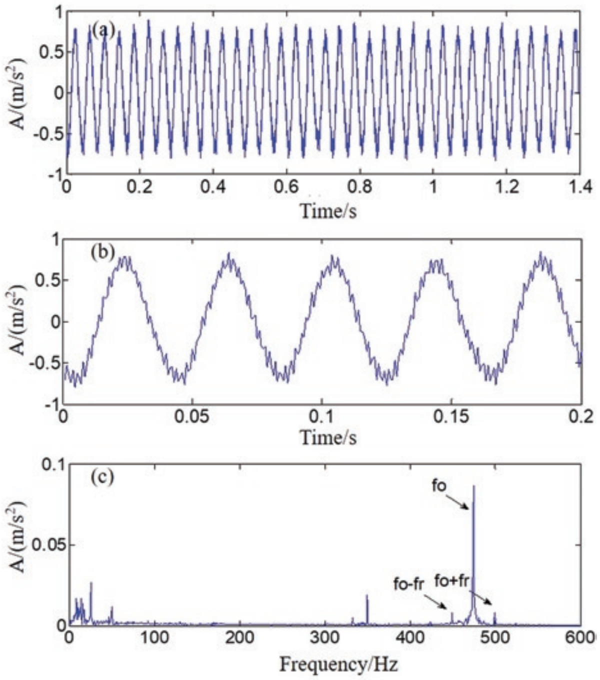

Fig. 11. The analysis of denoising results of NLM in case study 2: (a) denoising signal, (b) local amplification of the denoising signal and (c) envelope spectrum of denoising signal

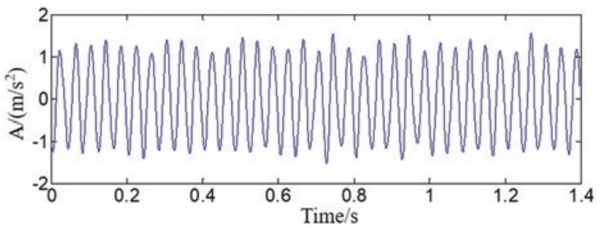

Fig. 12. The results of Wden in case study 2

components, providing convenience for rapid and accurate fault diagnosis. For comparison, the denoising waveform of wavelet threshold methods is shown in Fig. 12. Due to the problem of threshold selection, all the high frequency fault information is filtered out, only leaving smooth rotating frequency component, which cannot provide effective diagnostic information.

The effectiveness of NLM can be verified by the two case studies in real multistage centrifugal pump unit. Although this work only focuses on multistage centrifugal pump unit, the feature modes and characteristics are similar to other rotating machineries, such as wind turbine and stream turbine. For rotor-related faults, the harmonic frequencies components are is superimposed upon the rotating frequency component. For bearing and gear faults, the impulses and resonance components in high frequency are generally induced. Overall, the fault features appear periodically, and a large amount of similar information exist in the vibration signal of rotating machineries. Consequently, by comparing the local neighborhoods, finding the similar features on the basis of self-similarities, and removing the redundancy of similar patches, NLM is significantly suitable for analyzing the vibration signals of rotating machinery. Moreover, different from the decomposition-based denoising methods, there are no need of selecting basis function and setting complex decomposed parameters in NLM, providing an accessible denoising approach for practical application.

6. Conclusions

Noise reduction of mechanical vibration signal is the key and difficult point to realize accurate fault diagnosis. Considering the nonstationary characteristics of vibration signal and the difficulty of selecting the threshold value in wavelet denoising methods, this paper investigates vibration signal denoising of multistage centrifugal pump unit using NLM. Different from the traditional denoising idea of basis function decomposition, NLM uses the weighted average of similar signal blocks in a neighborhood, which has strong non-stationary signal processing ability and excellent adaptability. Moreover, this method has a wide application prospect because of its simple principle and easy parameter selection. The validity and superiority of the method are verified by the simulation signal analysis. The key parameter selections are also discussed. The analysis results of practical diagnosis cases of multistage centrifugal pump show that NLM can effectively filter the noise components with poor correlation between signal blocks and enhance the periodic fault characteristics.

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References

1. An X and Yang J. Denoising of hydropower unit vibration signal based on variational mode decomposition and approximate entropy. Transactions of the Institute of Measurement and Control 2016; 38: 282-92, https://doi.org/10.1177/0142331215592064.
2. Buades A, Coll B, Morel J M. A Non-Local Algorithm for Image Denoising[C]// Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on IEEE 2005; 2 :60-65.
3. Darbon J, Cunha A, Chan T F. Fast nonlocal filtering applied to electron cryomicroscopy in IEEE International Symposium on Biomedical Imaging: From Nano To Macro. IEEE 2008:1331-1334, https://doi.org/10.1109/ISBI.2008.4541250.
4. Duan R, Lin Y, Zeng Y. Fault diagnosis for complex systems based on reliability analysis and sensors data considering epistemic uncertainty. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2018; 20(4): 558-566, https://doi.org/10.17531/ein.2018.4.7.
5. Guo-dong Yue, Xiu-shi Cui, Yuan-yuan Zou, Xiao-tian Bai, Yu-Hou Wu, Huai-tao Shi. A Bayesian wavelet packet denoising criterion for mechanical signal with non-Gaussian characteristic. Measurement 2019, 138: 702-712, https://doi.org/10.1016/j.measurement.2019.02.066.
6. Han T, Jiang DX, Zhao Q, Wang L and Yin K. Comparison of random forest, artificial neural networks and support vector machine for intelligent diagnosis of rotating machinery. Transactions of the Institute of Measurement and Control 2018; 40: 2681-2693, https://doi.org/10.1177/0142331217708242.
7. Hernandezsolis A, Carlsson F. Diagnosis of Submersible Centrifugal Pumps: A Motor Current and Power Signature Approaches. Epe Journal European Power Electronics & Drives 2010; 20(1): 58-64, https://doi.org/10.1080/09398368.2010.11463749.

8. Junchao Guo, Dong Zhen, Haiyang Li, Zhanqun Shi, Fengshou Gu, Andrew.D. Ball. Fault feature extraction for rolling element bearing diagnosis based on a multi-stage noise reduction method. Measurement 2019; 139: 226-235, https://doi.org/10.1016/j.measurement.2019.02.072.
9. Kaluer S, Fekete K, Jozsa L, Klai Z. Fault diagnosis and identification in the distribution network using the fuzzy expert system. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2018; 20(4): 621-629, https://doi.org/10.17531/ein.2018.4.13.
10. Kai Zheng, Jiufei Luo, Yi Zhang, Tianliang Li, Jiafu Wen, Hong Xiao. Incipient fault detection of rolling bearing using maximum autocorrelation impulse harmonic to noise deconvolution and parameter optimized fast EEMD. ISA Transactions 2019; 89: 256-271, https://doi.org/10.1016/j.isatra.2018.12.020.
11. Li, H., Bao, T., Gu, C., Chen, B. Vibration feature extraction based on the improved variational mode decomposition and singular spectrum analysis combination algorithm. Advances in Structural Engineering 2019, 22(7): 1519-1530, https://doi.org/10.1177/1369433218818921.
12. Li Y, Wang X, Liu Z, Liang X, Si S. The entropy algorithm and its variants in the fault diagnosis of rotating machinery: A review. IEEE Access 2018, 6: 66723-66741, https://doi.org/10.1109/ACCESS.2018.2873782.
13. Li Y, Wang X, Si S, Huang S. Entropy based fault classification using the Case Western Reserve University data: A benchmark study. IEEE Transactions on Reliability 2019, 1-14, https://doi.org/10.1109/TR.2019.2896240.
14. Milu Zhang, Tianzhen Wang, Tianhao Tang, Mohamed Benbouzid, Demba Diallo. An imbalance fault detection method based on data normalization and EMD for marine current turbines. ISA Transactions 2017; 68: 302-312, https://doi.org/10.1016/j.isatra.2017.02.011.
15. Saba Adabi, Siavash Ghavami, Mostafa Fatemi, Azra Alizad. Non-Local based denoising framework for in vivo contrast-free ultrasound microvessel imaging. Sensors; 19(2): 245, https://doi.org/10.3390/s19020245.
16. Salman A H , Ahmadi N , Mengko R. Performance Comparison of Denoising Methods for Heart Sound Signal. 2015 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS). IEEE, 2015, https://doi.org/10.1109/ISPACS.2015.7432811.
17. Sikora M, Szczyrba K, Wróbel, Michalak M. Monitoring and maintenance of a gantry based on a wireless system for measurement and analysis of the vibration level. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2019; 21(2): 341-350, https://doi.org/10.17531/ein.2019.2.19.
18. O.I. Traore, L. Pantera, N. Favretto-Cristini, P. Cristini, S. Viguier-Pla, P. Vieu. Structure analysis and denoising using singular spectrum analysis: Application to acoustic emission signals from nuclear safety experiments. Measurement 2017, 104: 78-88, https://doi.org/10.1016/j.measurement.2017.02.019.
19. Ou D, Tang M, Xue R, Yao H. Hybrid fault diagnosis of railway switches based on the segmentation of monitoring curves. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2018; 20(4): 514-522, https://doi.org/10.17531/ein.2018.4.2.
20. Te Han, Dongxiang Jiang, Nanfei Wang. The fault feature extraction of rolling bearing based on EMD and difference spectrum of singular value. Shock and Vibration 2016: 5957179, https://doi.org/10.1155/2016/5957179.
21. Tracey B H, Miller E L. Nonlocal means denoising of ECG signals. IEEE Transactions on Bio-medical Engineering 2012; 59(9): 2383, https://doi.org/10.1109/TBME.2012.2208964.
22. Ville D V D, Kocher M. SURE-Based Non-Local Means. IEEE Signal Processing Letters 2009; 16(11): 973-976, https://doi.org/10.1109/LSP.2009.2027669.
23. Wu Ding-hai, Zhang Pei-lin, Yang Wang-can, Qi Yun-guang. Overlappling group thresholding denoising method based on dual-tree complex wavelet packet transform. Journal of Vibration and Shock 2016; 35(10): 162-166.
24. Yang Shaopu, Zhao Zhihong. Improved Wavelet Denoising Using Neighboring Coefficients and Its Application to Machinery Fault Diagnosis. Journal of Mechanical Engineering 2013; 49(17): 137-141, https://doi.org/10.3901/JME.2013.17.137.
25. Yu G, Yin Y, Wang H, et al. Image denoising based on Non-Local means and multi-scale dyadic wavelet transform in IEEE International Conference on Computer Science and Information Technology. IEEE 2010: 333-336.
26. Yongbo Li, Yuantao Yang, Guoyan Li, Minqiang Xu, Wenhu Huang. A fault diagnosis scheme for planetary gearboxes using modified multi-scale symbolic dynamic entropy and mRMR feature selection. Mechanical Systems and Signal Processing 2017, 91: 295-312, https://doi.org/10.1016/j.ymssp.2016.12.040.
27. Zhang Long, Hu Junfeng, Xiong Guoliang. Fault diagnosis of rolling bearings based on weighted nonlocal means algorithm. Journal of Vibration and Shock 2016; 35(19): 156-161, https://doi.org/10.1155/2016/4805383.
28. Zhanxiong Wu, Thomas Potter, Dongnan Wu, Yingchun Zhang. Denoising high angular resolution diffusion imaging data by combining singular value decomposition and non-local means filter. Journal of Neuroscience Methods 2019; 312: 105-113, https://doi.org/10.1016/j.jneumeth.2018.11.020.
29. Zhiwen Liu, Zhengjia He, Wei Guo, Zhangchun Tang. A hybrid fault diagnosis method based on second generation wavelet de-noising and local mean decomposition for rotating machinery. ISA Transactions 2016; 61: 211-220, https://doi.org/10.1016/j.isatra.2015.12.009.

Te HAN
Dongxiang JIANG
Department of Energy and Power Engineering
Tsinghua University
Beijing, 100084, China

E-mail: hant15@mails.tsinghua.edu.cn, jiangdx@tsinghua.edu.cn