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Article

Adaptive parameter-optimized NLM algorithm to denoise vibration signals of hydropower units

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Abstract: Monitoring and diagnosing the operating state of hydropower units is crucial, which becomes a hot research topic in the industry. the vibration signals provide a reliable indication to detect the abnormal working conditions of hydropower units. however, the vibration signals is affected by the environment noise inevitably, making it difficult to truly reflect the operating state of hydropower units. the non-local means (NLM) algorithm is proved to be effective in denoising the vibration signals, however, whose parameters depend on the human experience, which hinders its application and development. in the present work, based on the Bayesian parameter optimization (BPO), the parameters of NLM are set adaptively, the BPO-NLM denoising algorithm is proposed. by conducting the simulation, the denoising effectiveness of BPO-NLM is improved remarkably than that of the traditional NLM. at different snr, RMSE of the signal denoised by BPO-NLM is much smaller than that of the traditional NLM, while snr of the signal denoised by BPO-NLM is much larger, namely, the effective component of the signal is enhanced, while the noise component is suppressed.

Keywords: Bayesian parameter optimization; non-local means algorithm; denoising vibration signals; monitor and diagnose operating status

1. Introduction

Hydropower units are high safety equipment for energy conversion and play an important role in the country's dual carbon strategy. With the development of the economy and society, the requirements for the safety, reliability, and stability of hydropower units are becoming increasingly high. However, the operating environment of hydropower units is relatively complex, which poses a great threat to their safe and stable operation. How to effectively monitor and diagnose the operating status of hydropower units is currently a hot research topic in the industry [1,2]. Based on relevant research, nearly 80% of faults in hydropower units can be reflected in equipment vibration [3,4]. Therefore, by monitoring and diagnosing the vibration signals of hydropower units online, abnormal equipment conditions can be detected in a timely manner, thereby ensuring the safe and stable operation of hydropower units [5,6], and providing reliable basis for subsequent fault diagnosis work.

The vibration signal of hydropower units is one of the important indicators for evaluating the operating status of hydropower units [7,8]. It is itself a non-linear and non-stationary signal, and in addition, signal acquisition is generally affected by the noise generated by equipment operation, making it difficult for the sampled signal to directly and truly reflect the operating status of hydropower units. Therefore, it is necessary to denoise the vibration signals of hydropower units and obtain real information, and different signal denoising algorithms are proposed by researchers [9–12]. Traditional Fourier transform is more suitable for linear signal analysis of stationary rules [13,14], while wavelet analysis can perform corresponding non-stationary signal analysis, however, its parameter settings lack self-adaptability [15,16]. The non-local means (NLM) algorithm is one of the emerging denoising algorithms, which has aroused the research interest of many scholars. Originally, the NLM algorithm is mainly applied to the noise removal of two-dimensional images, which exhibits the potential capability in denoising one-dimensional signals [17,18]. Tracey and Miller [18] successfully applied NLM to denoise one-dimensional medical electrocardiogram signals for the first time in 2012, proving that this scheme can effectively improve signal-to-noise ratio and the denoising effect is no different from the widely used wavelet analysis in the past. Lv et al. [19] addressed the slow computational speed of NLM by using a fast NLM algorithm that reduces one cycle and combined it with envelope spectrum analysis to achieve fault diagnosis of rolling bearings. Based on the evaluation indicators of signal-to-noise ratio, distortion rate, and mean square error, NLM denoising performs better than other commonly used methods, such as wavelet soft threshold denoising, empirical mode decomposition denoising, wavelet denoising and singular value decomposition denoising. Furthermore, Lv et al. [20] proposed a new method for fault diagnosis of rolling bearings based on multivariate empirical mode decomposition in 2016. This method uses NLM to preprocess multivariate signals, and then selects effective IMF components for fault feature extraction using fault correlation coefficients. Van et al. [21] combined the NLM algorithm with empirical mode decomposition (EMD) to achieve fault diagnosis of rolling bearings. This is the first proposal to apply NLM to denoise bearing vibration signals. The experiment showed that NLM and processed vibration signals can effectively overcome the noise sensitivity of EMD and enhance EMD performance. At the same time, the article also proved that using NLM is more effective than discrete wavelet denoising (DWT denoising). Van et al. [22] once again applied NLM to fault diagnosis of rolling bearings, extracting features using EMD. In the subsequent two-stage feature selection, a new method was used, which mixed distance evaluation technology (DET) and particle swarm optimization (PSO) algorithm. This work also proposed for the first time a study on the sensitivity of classifiers to redundant and irrelevant features, and conducted comparative experimental analysis using K-nearest neighbor regression, probabilistic neural networks and support vector machines (SVM). Laha [23] improved NLM and proposed a fast maximum peak non local mean algorithm for diagnosing rolling bearing faults. This method is simple and feasible, and the parameters are determined by maximizing the peak value of the time series. The experimental results show that this method can effectively extract the impact signal that is submerged in noise, and has better performance than minimum entropy deconvolution.

The effectiveness of the NLM algorithm in denoising one-dimensional signals has been widely verified by previous researchers. The decisive parameters of the NLM algorithm are half width of target and similar structural blocks P, half width of the search area centered on the signal point to be restored K and filter parameter λ, which greatly affect the effectiveness of the algorithm in denoising one-dimensional signals [24]. However, the setting of these parameters still heavily depends on human experience, which hinders the further development and application of the NLM algorithm. In the present work, we try to improve the NLM algorithm to denoise vibration signals of hydropower units, where the decisive parameters of the NLM algorithm are set adaptively based on Bayesian parameter optimization, improving the effectiveness of NLM in denoising one-dimensional signals.

The present work is organized as follows. Firstly, the NLM algorithm and its decisive parameters are introduced briefly. Next, the improved NLM algorithm based on Bayesian parameter optimization is pro- posed. Then, the simulation is conducted, where the effectiveness of the improved NLM algorithm based on Bayesian parameter optimization in denoising vibration signals of hydropower units is validated. Finally, the present work is summarized.

2. NLM algorithm

The non-local means filtering algorithm utilizes the characteristics of numerous similar structures in images to achieve image denoising by performing weighted averaging on these similar structures. As a result, the NLM algorithm has been significantly used for two-dimensional image denoising [25,26]. However, these similar characteristics also exist in one-dimensional signals, and the NLM algorithm has been successfully applied to one-dimensional rolling bearing vibration signal processing [27,28]. Therefore, the NLM algorithm can also be used to process vibration signals of hydropower units. The present work uses the NLM algorithm to preprocess and denoise the vibration signals of hydropower units, in order to facilitate subsequent signal feature extraction.

Assuming that the actual vibration acquisition signal of a noisy hydropower unit y is the superposition of the real vibration signal u and external interference noise n, namely,

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

The NLM algorithm calculates the weighted average of all similar blocks to estimate the true signal $u^*(s)$, namely,

$$u^*(s) = \frac{1}{Z(s)} \sum_{t \epsilon D(s)} \omega(s,t) y(t) \tag{2}$$

where $Z(s) = \sum_{t \epsilon D(s)} \omega(s,t))$ is the normalization factor, which represents the sum of the similarity of all search blocks, $D(s)$ represents the set of all points within the search range,

$$\omega(s,t) = \exp\,(\frac{-\sum_{\delta \epsilon \Delta} (y(s+\delta) - y(t+\delta))^2}{2 L_\Delta \lambda^2} \tag{3}$$

represents the weight, which refers to the similarity between two search blocks centered on s and t, and must satisfy the basic conditions of $0 \leq \omega\ (s,\ t)/Z\ (s) \leq 1$ and $\sum_t \omega(s,t) = 1$, where λ is the bandwidth parameter of the filter, which affects the smoothness of the denoised signal, $\triangle$ is represented by the search block in the center, K is taken as half of the length of $\triangle$ region, which affects the computational complexity and time of the algorithm, $L \triangle = 2P + 1$ is a neighborhood block centered on s, which affects the similarity of structural blocks discovered during algorithm operation quantity. The parameters λ, K and P are the decisive parameters of the NLM algorithm, which greatly affect its performance in denoising one-dimensional signals, however, the setting of these parameters still relies heavily on human experience.

3. Bayesian parameter optimization

Bayesian optimization was first proposed by Snoke et al. [29] in 2012 for optimizing hyperparameters in machine learning models. The essence is to estimate the optimal value of a function based on existing sampling points when the function equation is unknown. The problem of considering extreme values is represented as

$$x^* = \arg \min_{x \epsilon R^d} f(x) \tag{4}$$

where the decision function $f(x)$ is optimized within the range R^d, and x represents the decision vector in the d-dimensional space. Bayesian optimization only requires specifying the objective function to be optimized (a generalized function that only requires specifying input and output), and updating the posterior distribution of the objective function by continuously adding sample points. Bayesian optimization has unique advantages over conventional network global and random searches, where Bayesian calls on Gaussian processes to fit the optimization objective function $f(x)$, while traditional algorithms require the objective function to be a known mathematical model and simple calculation without involving human intervention. Many practical problems do not meet these prerequisites, resulting in weak adaptability of traditional optimization algorithms. However, Bayesian optimization does not have a hard requirement for the objective function $f(x)$, and considers the continuous updating of prior information in the previous step, while traditional methods do not consider the previous parameter information. Traditional methods are prone to obtaining local optima when dealing with non convex problems, while Bayesian optimization is still very effective for non convex problems and can obtain global optimal solutions. Bayesian optimization consists of two parts, namely, a Gaussian process and an extraction function. The Gaussian process is called to simulate an optimization function with unknown form. After obtaining the posterior probability of the function through the Gaussian process, the extraction function samples new points based on certain indicators of this posterior probability. Placing the sampled new points into the observation data as a reference for the next calculation can describe a more accurate posterior probability.

Compared to other hyperparameter optimization algorithms such as grid search, random search, genetic algorithm, particle swarm optimization, Bayesian optimization requires fewer initial sample points and has higher optimization efficiency, making it more suitable for model hyperparameter tuning scenarios. The selection of parameters has always been a research focus of NLM denoising algorithms, but current research results do not have objectivity and rely heavily on manual experience, which also hinders the further development and application of NLM algorithms. In order to better improve the NLM denoising algorithm and achieve effective denoising in high noise backgrounds, the present work proposes to introduce Bayesian optimization into the setting of the key parameters of the algorithm, and find the optimal solution for the half width of the search domain K, half width of the structural block P and bandwidth parameter λ. Bayesian optimization hyperparameters require a given objective function, and the selection of the objective function can directly determine the result of parameter selection, thereby affecting the performance of algorithm denoising. The present work proposes combining spectral kurtosis and peak signal-to-noise ratio as the objective function for Bayesian optimization. In the fault diagnosis of rotating machinery equipment, kurtosis values are often used, but kurtosis as an overall indicator cannot reflect the impact of changes in characteristic signal com- ponents. To overcome the drawbacks of kurtosis, Dwyer [30] first proposed the concept of spectral kurtosis, followed by Antoni et al. [31] conducted further research on spectral kurtosis and provided a detailed explanation, including the definition, algorithm flow, and application conditions of spectral kurtosis. The spectral kurtosis is sensitive to the periodic instantaneous pulse signals caused by faults in the vibration signals of rolling bearings, and the peak signal-to-noise ratio is a commonly used indicator to evaluate the denoising effect. Therefore, the present work combines the two as the objective function of Bayesian optimization hyperparameters, which can effectively suppress the noise component of the original signal and enhance the useful part of the signal.

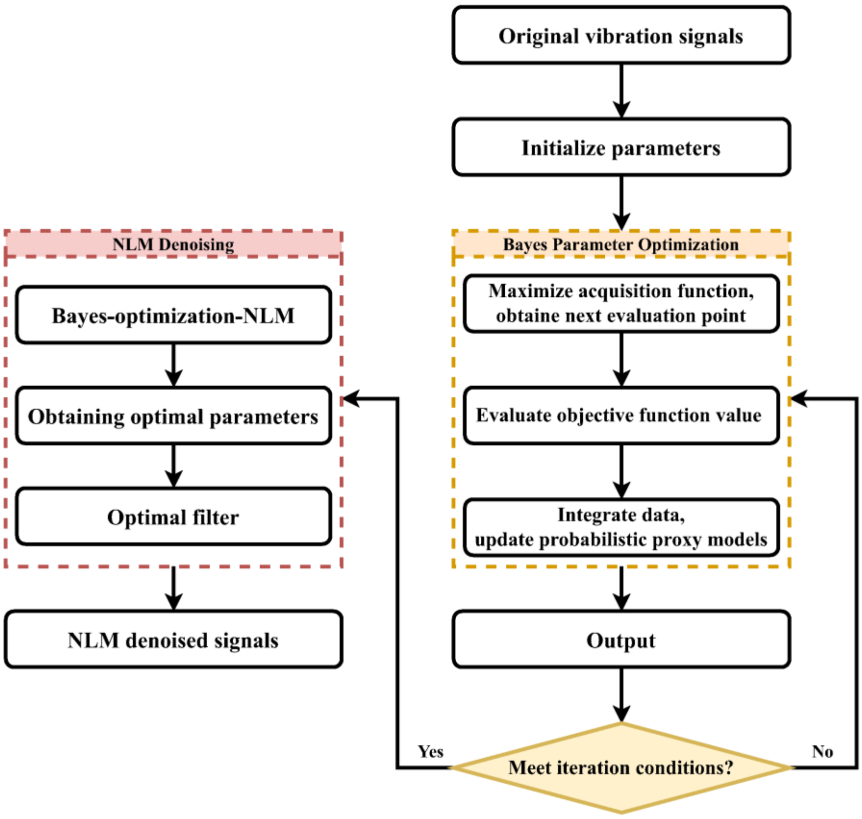


Figure 1. Flow chart of NLM denoising algorithm based on Bayesian parameter optimization.

The optimization objective function is

$$-\alpha \max(KYRT) - \beta PSNR + \lambda MEAN \tag{5}$$

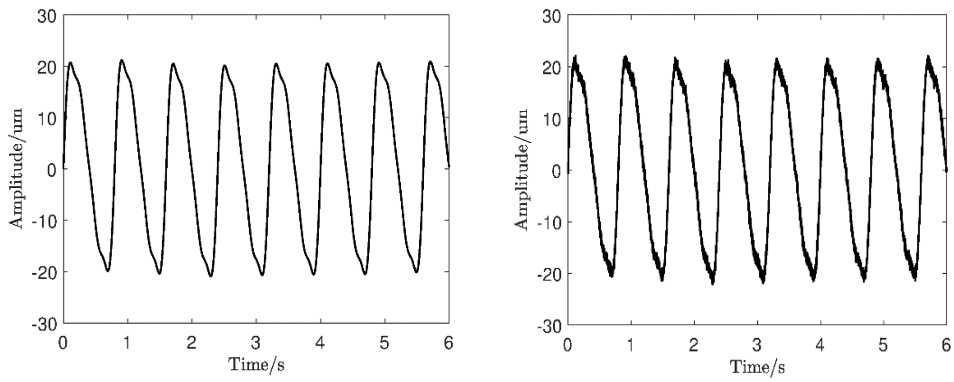
where *KYRT* represents the spectral kurtosis value, *PSNR* is the peak signal-to-noise ratio, and *MEAN* is the mean square error. The experimental results show that it is more effective than using spectral kurtosis or peak signal-to-noise ratio as the objective function alone. The algorithm flowchart for introducing Bayesian optimization into NLM denoising is shown in **Figure 1**.

4. Results and discussions

The swing signal of hydropower units is an important monitoring indicator. To verify the effectiveness of the NLM algorithm based on Bayesian parameter optimization in denoising vibration signals, the present work selects the swing signal of hydropower units for simulation analysis. The swing of hydropower units is mainly affected by mechanical excitation and hydraulic excitation. Mechanical excitation is generally dominated by medium frequency (1, 2, and 3 times the rotational frequency), while hydraulic excitation is mainly dominated by low frequency (0.2 0.45 times the rotational frequency). Therefore, a simulation signal is constructed by [32].

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

where $A_i = 1; 2; 3; 4; 5; 6 = 20,\ 4.5,\ 2.55,\ 1.5,\ 0.4$ and 0.3 um, $f_i = 1; 2; 3; 4; 5; 6 = 1.25,\ 1.25 \times 2,\ 1.25 \times 3,\ 1.25 \times 4,\ 1.25 \times 0.2$ and 1.25×0.3. The sampling frequency is set to be 1000. Overlay a Gaussian white noise with a signal-to-noise ratio of 5 dB on the original signal without noise. The simulation signals without and with noise are shown in **Figure 2**.



(a) Without Noise **(b)** With Noise

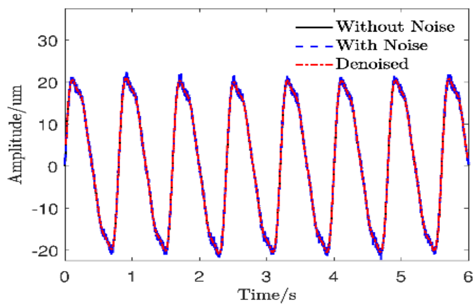
Figure 2. Simulation signals without **(a)** and with **(b)** noise.

To evaluate the effectiveness of NLM based on Bayesian parameter optimization in denoising vibration signals, the root mean square error RMSE and signal-to-noise ratio SNR are defined, namely,

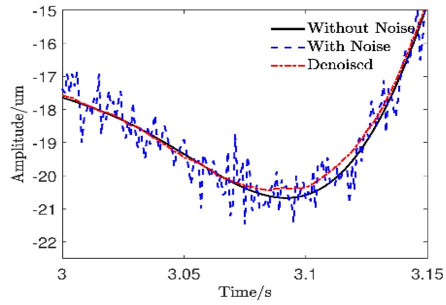
$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2} \tag{7}$$

$$SNR = 10lg\frac{\sum_{i=1}^{N} {x_i}^2}{\sum_{i=1}^{N}(y_i - x_i)^2} \tag{8}$$

where N is the sampling point number, x_i is the original signal without noise, and y_i is the denoised signal. The smaller RMSE is, the larger SNR is, and the superior the effectiveness of the algorithm in denoising vibration signals. **Figure 3** compares the signals without/with noise and the denoised signal with NLM, where the algorithm parameters are $\lambda = 0.3\sigma$ (σ is the standard error of the signal with noise), K = 20 and P = 12.



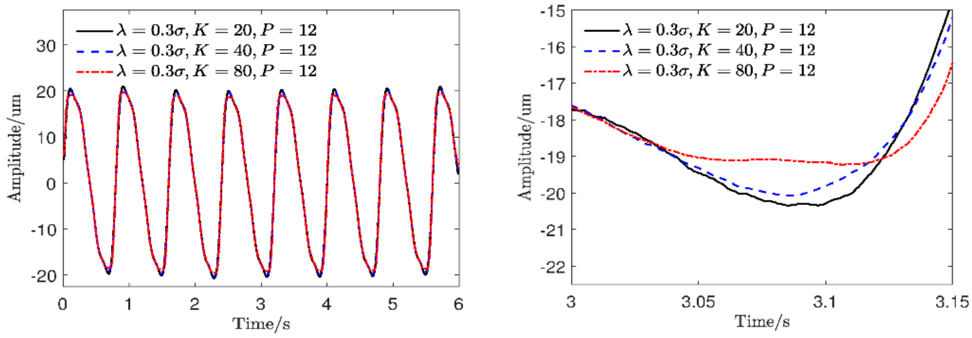
(a) full.



(b) part.

Figure 3. Comparison among the signals without/with noise and the denoised signal with NLM.

The effectiveness of NLM in denoising vibration signals is significant, compared to the signal with noise, which is contaminated by the noised obviously, while the denoised signal is relatively smooth, which is very close to the signal without noise. Furthermore, the differences among the signals without/with noise and the denoised signal is enlarged, though the effectiveness of NLM in denoising vibration signals is satisfactory, the difference between the signal without noise and the denoised signal is not to be ignored, which is relevant to the algorithm parameters closely. To validate the effect of the parameter setting on the denoising effectiveness, three different parameters are adopted, namely, $\lambda = 0.3\sigma$, K = 20/40/80 and P = 12. **Figure 4** compares the denoised signals by NLM with different algorithm parameters. Clearly, with different algorithm parameters, the denoising effectiveness of NLM is affected greatly. Furthermore, to evaluate the denoising effectiveness quantitatively, RMSE and SNR of three algorithm parameters are calculated, which are listed in **Table 1**. With the increase of the parameter K, namely, the half width of the search domain, RMSE of the denoised signal becomes larger, while SNR becomes smaller, the denoising effectiveness becomes worse. Among the three algorithm parameters, $\lambda = 0.3\sigma$, K = 20, P = 12 is the best, in which RMSE is the smallest while SNR is the largest. The parameter setting affects the denoising effectiveness significantly, how to find the optimal algorithm parameter is the problem to be solved.

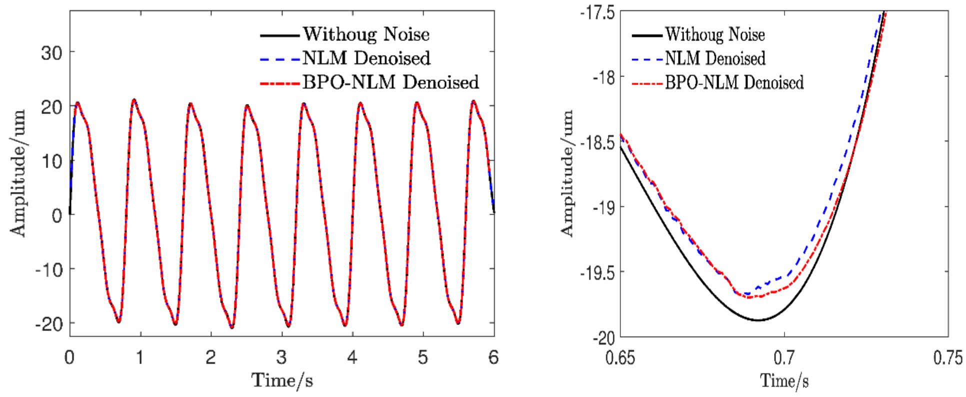


(a) full. **(b)** part.

Figure 4. Comparison among the denoised signals by NLM with different algorithm parameters.

Table 1. RMSE and SNR of three algorithm parameters.

	λ = 0.3σ, K = 20, P = 12	λ = 0.3σ, K = 40, P = 12	λ = 0.3σ, K = 80, P = 12
RMSE	0.1448	0.3022	0.6815
SNR	40.125	33.733	26.669



(a) full **(b)** part

Figure 5. Comparison of the denoising effectiveness between traditional NLM and BPO-NLM (NLM based on Bayesian parameter optimization).

The Bayesian optimization provides a solution to set the parameters of NLM adaptively, which is independent on the expert experience. **Figure 5** compares the denoising effectiveness between traditional NLM and BPO-NLM (NLM based on Bayesian parameter optimization). Compared to the traditional NLM, whose parameters depend on the user experience, the denoising effectiveness of BPO-NLM is improved greatly. We should point out that the algorithm parameters of the traditional NLM are selected, namely, λ = 0.3σ, K = 20, P = 12, which is of the superior denoising effectiveness in the previous study, while the optimal parameters are λ = 1.4632, K = 20, P = 50. Clearly, the BPO-NLM denoised signal is closer to the original signal without noise, and it is much smoother than the signal denoised by the traditional NLM. To compare the denoising effectiveness between the traditional NLM and BPO-NLM quantitatively, RMSE and SNR of the denoised signals are listed in **Table 2**. Compared to the traditional NLM, RMSE of the signal denoised by BPO-

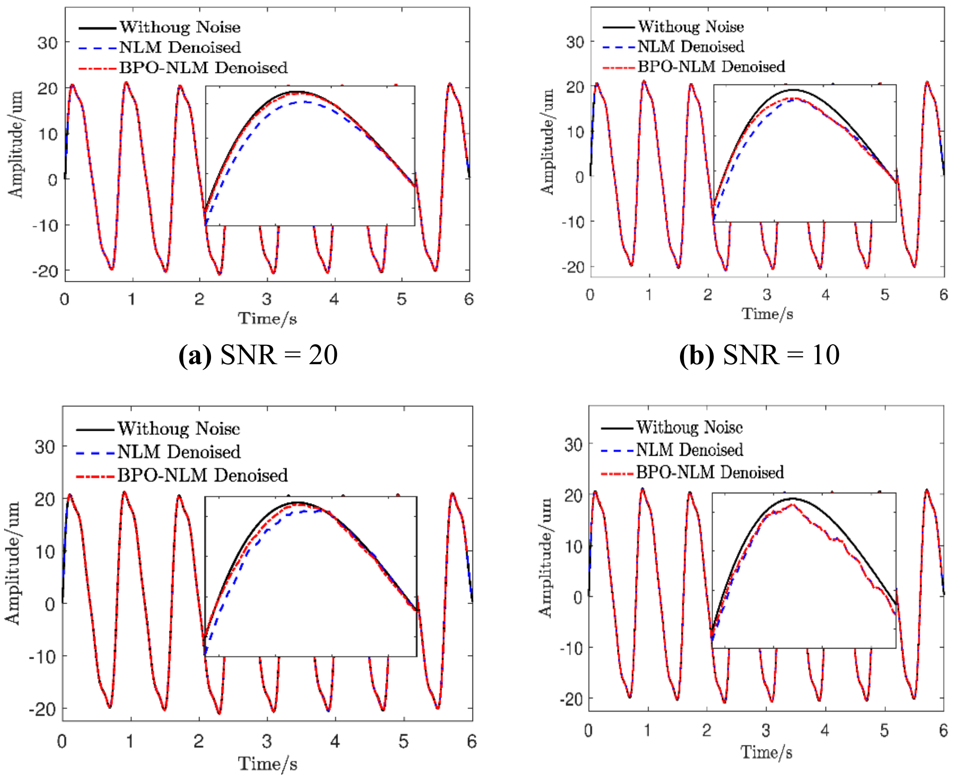
NLM is decreased by 21.9%, while SNR is improved by 5.3%, the denoising effectiveness is improved greatly.

Table 2. RMSE and SNR of signals denoised by the traditional NLM and BPO-NLM.

	Traditional NLM Denoised Signal	BPO-NLM Denoised Signal	Relative Error (%)
RMSE	0.1273	0.0994	21.9
SNR	41.238	43.439	5.3

Furthermore, we study the denoising effectiveness of BPO-NLM under different SNR. **Figure 6** shows the denoising effectiveness of BPO-NLM under different SNR. No matter how much SNR is, the signal denoised by BPO-NLM is closer to the original signal without noise, namely, the error between the denoised signal and the original signal is smaller. Therefore, the BPO-NLM denoising algorithm is effective to the general vibration signals. Meanwhile, with the increase of SNR, the original signal is distorted more sevely by the environment noise, the denoised signal by BPO-NLM is smoother than that by the traditional NLM. Furthermore, RMSE and SNR of the denoised signals under different SNR are calculated, which are shown in **Figure 7**. Obviously, compared to the traditional NLM, RMSE of the signals denoised by BPO-NLM are much smaller, namely, the denoised signals are closer to the original signals without noise. At the same time, with the increase of SNR, RMSE of the signals denoised by BPO-NLM decrease rapidly. SNR of the signals denoised by BPO-NLM are greater than those denoised by the traditional NLM, namely, the effective component of the signal is enhanced, while the noise component is suppressed. When SNR is low, the denoising effective of BPO-NLM is improved much remarkably, at SNR=20, SNR of the denoised signal is close to 55.

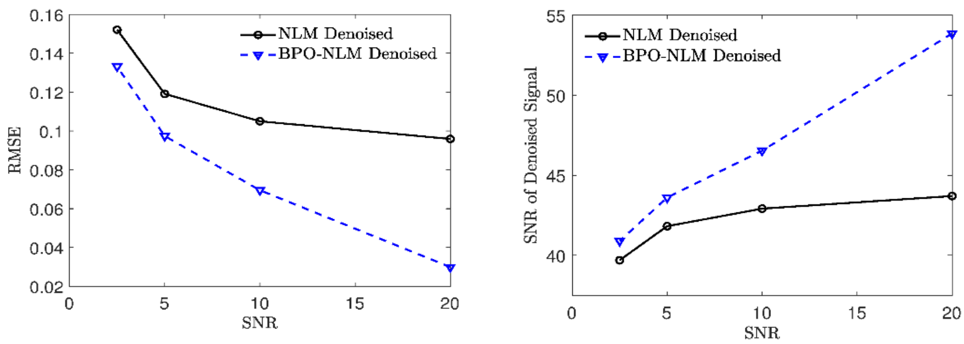
Lastly, how the algorithm parameters depend on SNR is investigated. **Figure 8** shows the optimal algo-rithm parameters by BPO-NLM under different SNR. As stated before, the decisive parameters of the NLM denoising algorithm are the bandwidth λ, half width of the search domain K and half width of the structural block P, which affect the denoising effectiveness of NLM significantly. Thus, how to set these parameters is crucial to denoise vibration signals. In the present work, Bayesian parameter optimization is introduced to set these parameters adaptively, which can improve the denoising effectiveness of NLM greatly. The bandwidth λ is insensitive to SNR, namely, at different SNR, the changes of λ is very smaller, thus, $\lambda = 1.463$ is suitable to most signals with noise. At low SNR, the half width of the search domain K remains constant, with the increase of SNR, K decreases dramatically, namely, a narrow search domain is suitable for the signals at high SNR. Interestingly, the dependence of the half width of the structural block P on SNR is nonmonotonic, at low SNR, with the increase of SNR, P increases rapidly, increasing SNR further, P decreases to the previous level, namely, at very low and high SNR, a narrow structural block is recommended, while a wide structural block is optimal for the signals at medium SNR.



(a) SNR = 20 **(b)** SNR = 10

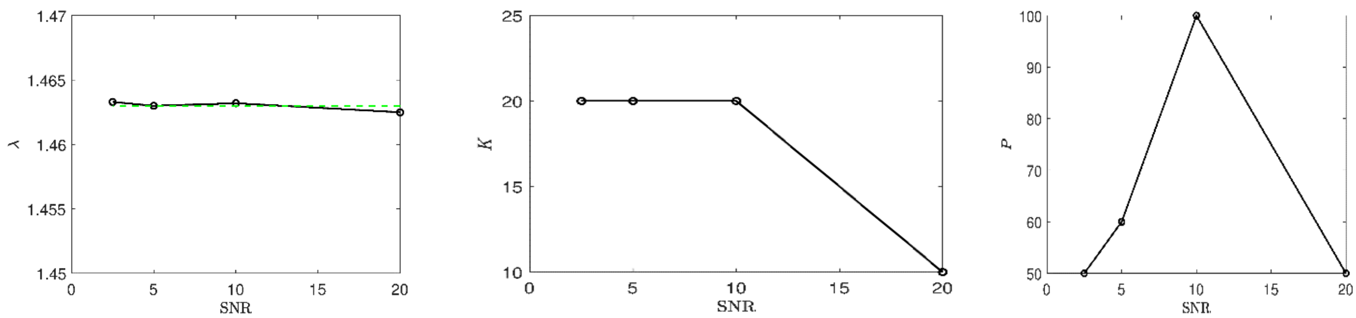
(c) SNR = 5 **(d)** SNR = 2.5

Figure 6. Comparison of the denoising effectiveness of BPO-NLM under different SNR.



(a) RMSE **(b)** SNR

Figure 7. RMSE and SNR of the denoised signals under different SNR.



(a) SNR **(b)** SNR **(c)** SNR

Figure 8. Optimal algorithm parameters by BPO-NLM under different SNR.

5. Conclusions

The present work proposes the BPO-NLM denoising algorithm, which utilizes the Bayesian parameter optimization to set the algorithm parameters adaptively, avoiding the interference of the human experience. Compared with the traditional NLM algorithm, whose parameters depends on the human experience, the denoising effectiveness is improved remarkably by BPO-NLM. At different SNR, RMSE of the signal denoised by BPO-NLM is much smaller than that by the traditional NLM, while SNR of the signal denoised by BPO- NLM is much larger, namely, the effective component of the signal is enhanced, while the noise component of the signal is suppressed. Based on the present work, the following conclusions are drawn:

1) the denoising effectiveness of BPO-NLM is much greater than that of the traditional NLM, whose parameters are optimized instead of the human experience;
2) with the optimal parameters adopted, RMSE of the denoised signal is much smaller, while SNR is much larger;
3) the dependence of the parameters on SNR is quite different, namely, λ is insensitive to SNR, with the increase of SNR, a smaller K is recommended, a larger P may be optional at medium SNR, otherwise, P should be smaller.

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Availability of data and materials: The experimental data used to support the finding of the present study is available from the corresponding author upon request.

Conflict of interest: The authors declare no conflict of interest.

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