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A Novel Denoising Method of Defect Signals based on Ensemble Empirical Mode Decomposition and Energy-based Adaptive Thresholding

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ABSTRACT

In order to ensure the safe operation of oil and gas production systems, real-time online defect detection can play an important role. Among them, the first-hand magnetic eddy current signals can effectively identify the defects existing in the oil and gas pipeline, thereby avoiding serious casualties and economic losses. Aiming at the noise interference problem in signals, this research proposes a comprehensive adaptive noise reduction method based on ensemble empirical mode decomposition (EEMD) method and an energy-based adaptive thresholding method. The detailed steps are as follows: Firstly, a noisy signal is randomly selected in the defect signal database, and then EEMD is carried out to obtain a series of intrinsic mode functions (IMFs). Secondly, the distances measure method and the probability density function are used to identify the high noise IMFs and the low noise IMFs. Thirdly, an energy-based adaptive thresholding method is used to remove the noise of the high noise IMFs. Finally, the signal is reconstructed by combining the low noise IMFs with the high noise IMFs after noise reduction. The result of the proposed noise reduction method is compared with the results of other conventional methods. It is superior to other noise reduction methods in terms of signal-to-noise ratio, mean square error and percent root mean square difference. Therefore, the proposed noise reduction method is efficient and lays a foundation for pattern recognition of pipeline corrosion defects.

Keywords: Adaptive thresholding, ensemble empirical mode decomposition, magnetic eddy current, noise reduction

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INTRODUCTION

At present, signal analysis and processing technology have made great progress, and it has been widely used in petroleum, petrochemical, aerospace, transportation, computer and other industrial fields. Traditional noise reduction methods mainly include Fourier transform, Winer filtering, wavelet transform and so on. The Fourier transform is analyzed by mapping the signal time domain to the frequency domain. It is very practical for stationary signals under the condition that the spectral characteristics of the noise are different from the spectral characteristics of the signal. Wiener Filtering is an improved noise reduction method, but the basic theory is still based on Fourier transform. It is only suitable for stationary linear signals, which is not well suited for engineering signals.

However, the actual signal is usually a non-stationary signal. A wavelet transform method can make the effective components and the noises in the non-stationary signal show different characteristics respectively. Among them, the selection of the wavelet base has a great influence on the noise reduction effect, so the wavelet noise reduction lacks self-adaptability. In order to accurately describe the variation of frequency with time, a better adaptive method of instantaneous frequency analysis is needed. Norden E. Huang proposed a new signal processing method, namely Empirical Mode Decomposition (EMD) (Huang et al., 1998).

In essence, the method can smoothen the complex signal. The result is a gradual decomposition of fluctuations or trends in signals of different scales, resulting in a series of data sequences of different feature scales. On this basis, Flandrin et al. (2004) proposed an idea of EMD-based filter bank, which was an adaptive combination of high-pass, low-pass, band-pass or band-stop filter by selecting the intrinsic mode function of the corresponding order (Flandrin et al., 2004). Wu and Huang (2004), proved that the EMD method had a wavelet-like binary filter characteristic through a large number of experiments. Boudraa and Cexus (2007) used different closed-value methods for filtering and reconstructing each IMF to achieve signal noise reduction.

EMD has the advantage of wavelet transform and solves the problem of wavelet base selection in wavelet transform (Boudraa et al., 2004). In theory, it can be used for any type of signal decomposition. It can convert complex signals into limited order intrinsic mode functions (IMFs). Each order IMF component contains a local characteristic of the original signal on different time scales, and the instantaneous frequency of any point is meaningful (Dybała & Zimroz, 2014). Compared with other methods, the empirical mode decomposition method has a better capability of nonstationary and nonlinear signal processing. Therefore, the EMD method will be studied in depth in this research. However, the EMD method still has some shortcomings, one of which is the modal aliasing problem.

In order to improve the problem of modal aliasing, many researchers have conducted a lot of in-depth research. Tan proposed a multi-resolution EMD method to suppress mode aliasing (Tan et al., 2001). The range of feature scales of each order IMF is defined so that the implied scale components causing mode aliasing are separated from other components. The experimental results show that the method is effective in suppressing mode aliasing, but it sacrifices the time-frequency adaptive property of empirical mode decomposition. Aijun et al. (2011) proposed a method of eliminating mode aliasing by adding high-frequency harmonics and then performing EMD decomposition, which effectively eliminated the mode aliasing phenomenon, but it was difficult to pick the high frequency and amplitude added (Aijun et al., 2011). Based on the shortcomings of the above EMD improvement methods, this research proposes to use EEMD to reduce the noise of magnetic eddy current defect signal. EEMD is an improved EMD algorithm proposed by Norden E. Huang, which effectively solves the mixing phenomenon of EMD. Although EEMD has some problems such as large computation, decomposition times and noise amplitude, the results obtained by EEMD to suppress modal aliasing are still acceptable (Zhang et al., 2010). On this basis, it still needs to solve some problems about how to select high noise IMF components efficiently and reasonably.

Therefore, some scholars proposed to use the correlation coefficient method and Kullback-Leibler (KL) divergence based on information theory to remove the invalid IMF components (Komaty et al., 2013). The threshold selection of the two methods is based on the experience of some signals. The correlation coefficient method has good adaptability and can be used for general faults. The disadvantage is that the discrimination degree is small, the differential effect is not obvious, and the signal near the threshold boundary is prone to misjudgment. The advantage of the KL divergence is that the degree of discrimination is large, and the different effect is obvious. The disadvantage is that the adaptability is poor and the sensitivity is large.

The purpose of this research is to develop an adaptive noise reduction method by using the EEMD method and energy-based adaptive thresholding optimization technology for filtering noise in the eddy current signals. In order to evaluate the noise reduction effect of the proposed method, it is common to use actual signals.

MATERIALS AND METHODS

The noise reduction method proposed in this research is composed of three main parts: EEMD method, IMFs selection, and energy-based adaptive thresholding. Among these approaches, EEMD can decompose the original signal into a set of intrinsic mode functions that reveals the physical connotation of the signal, and effectively suppress the problem of mode aliasing in empirical mode decomposition by means of noise-assisted analysis. IMFs selection is mainly composed of probability density function and distances measure to distinguish the high noise IMFs with low noise IMFs. Probability density function graph can preliminarily find out the similarity between the original signal and each IMF. The distance-based measure can further distinguish high-noise IMF components with low-noise

IMF components. The energy-based adaptive threshold can adaptively set a corresponding threshold according to the nature of each IMF energy. Finally, the final reconstructed signal Z(t) is obtained by combining the denoised high-noise IMF components with the low-noise IMF components (Figure 1).

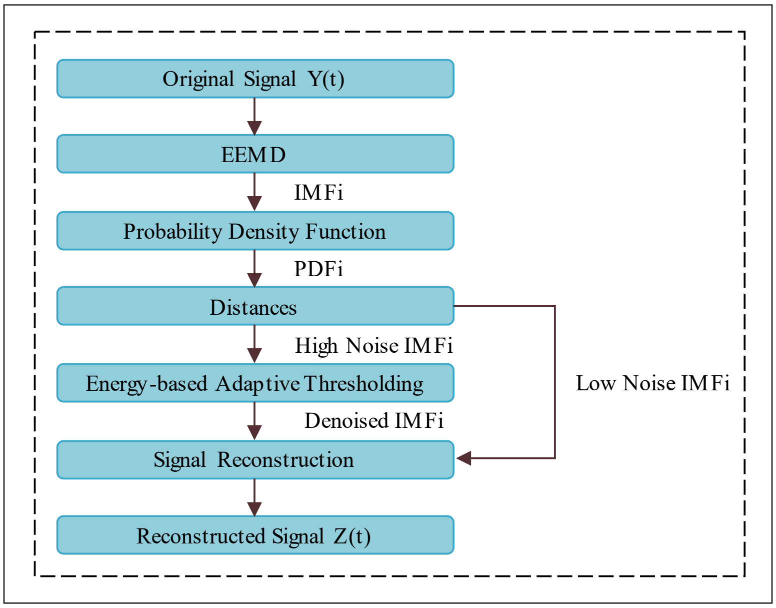

Figure 1. The procedure of the novel noise reduction method

Ensemble Empirical Mode Decomposition

The EMD algorithm can decompose a signal into several IMFs by filtering, and each IMF represents the intrinsic characteristic vibration form of the signal. The residual component reflects the trend of slow change in the signal. By analyzing each IMF, the feature information of the original data can be grasped more accurately and effectively. EMD has the characteristics of a binary filter bank, but this feature is destroyed because of mode aliasing problem. To solve this problem, Huang and Wu (2009) proposed the EEMD method.

The essence of EEMD is to add white noise to the original signal to smooth the abnormal signal and make use of the uniform distribution characteristic of the white noise spectrum to automatically distribute the signals on different time scales to the appropriate reference scales. Meanwhile, the decomposed IMFs will inevitably contain random noise signals. White noise has the characteristic of zero mean value. Multiple averages can make the noise offset each other, which can effectively suppress or even completely eliminate the influence of noise. That is, it is a multiple empirical mode decomposition of superimposed white Gaussian noise. The detailed steps of the EEMD algorithm are as follows:

1. Add a certain signal-to-noise ratio of white noise to the target signal $y(t)$.

   $$y_i(t) = y(t) + n_i(t) \qquad (1)$$

   Where,
   $y_i(t)$ is the signal after adding white noise for the *i*th time;
   $n_i(t)$ is the white Gaussian noise added for the *i*th time.

2. The EMD decomposition is performed on $y_i(t)$, and the corresponding IMF components and residual component are obtained. The signal is expressed as:

   $$y_i(t) = \sum_{j=1}^{n} c_{ij}(t) + r_i(t) \qquad (2)$$

   Where,
   $c_{ij}(t)$ is the *j*th component obtained by the *i*th decomposition.

3. Take the average value of IMF components $c_{ij}(t)$ as the final decomposition result of EEMD. The formula is as follows:

   $$c_j(t) = \frac{1}{M}\sum_{i=1}^{M} c_{ij}(t) \qquad (3)$$

   Where,
   $c_j(t)$ is the *j*th component of EEMD, *M* is the total number of EMD.

   Moreover, the frequency of added white Gaussian noise in EEMD obeys the following rule:

   $$\varepsilon_n = \frac{\varepsilon}{\sqrt{N}} \qquad (4)$$

   Where,
   ε_n is the error between the original signal and the signal resulting from the superposition of the final IMFs. ε is the amplitude of white Gaussian noise. It can be found that with the increase of the total number *N* of IMFs, the result of the final decomposition is closer to the real value.

4. The original signal $y(t)$ can be expressed as follows:

   $$y(t) = \sum_{i=1}^{n} c_j(t) + r_n(t) \qquad (5)$$

   Therefore, as shown in Figure 2, the magnetic eddy current signal of the pipeline is decomposed by EEMD.

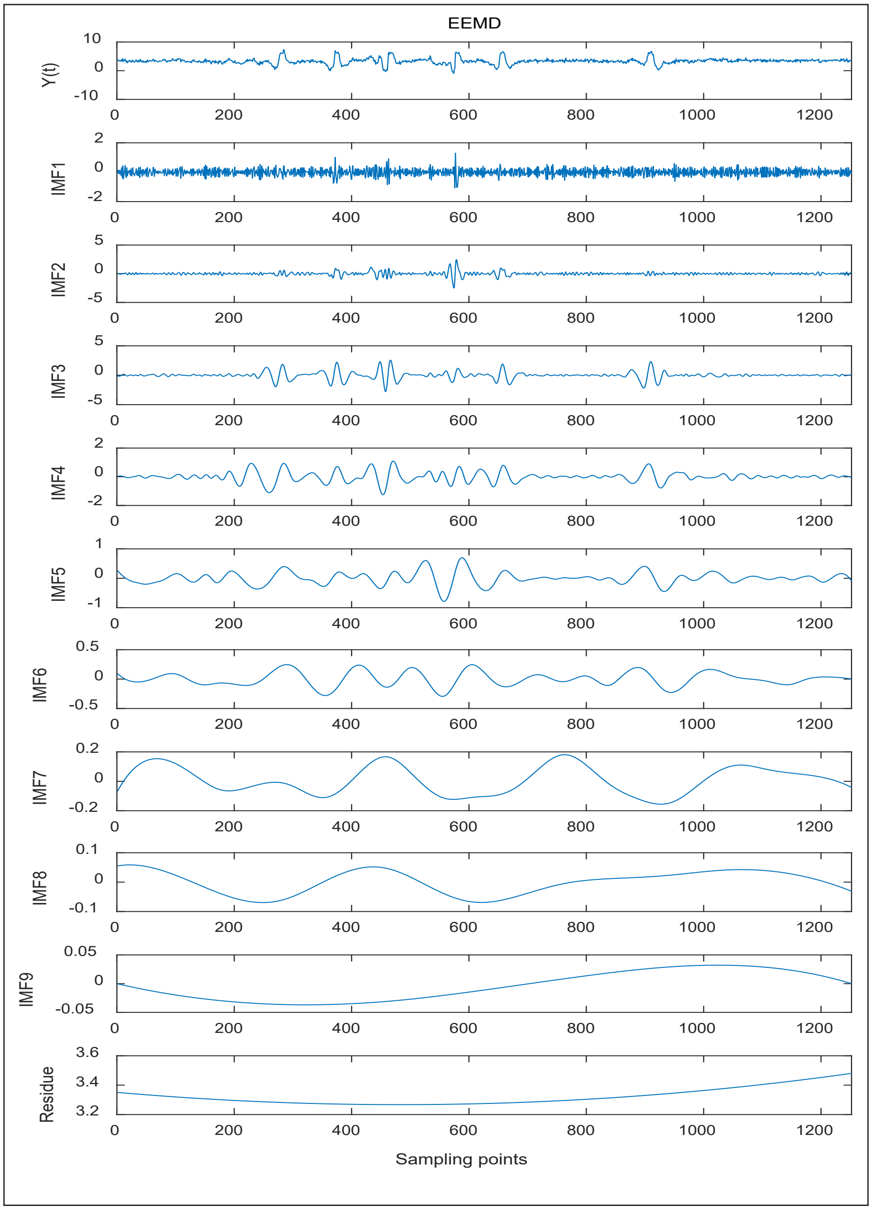

Figure 2. EEMD decomposition of original signal Y(t)

Measures

In the classification algorithm, it is widely used to calculate the distance between two input variables, that is, measurement. In some cases, the results of different measures are quite different from each other. Therefore, it is necessary to choose an appropriate measurement tool according to the characteristics of input data. The measure is composed of the similarity measures and distance measures (Xuecheng, 1992).

If the similarity degree of the two sample points in the similarity measure function is high, the similarity measure value is large. If the sample points are not similar, the similarity measure value is small. In this way, the similarity of sample points can be compared.

In the distance function, each sample point can be regarded as a point in the high-dimensional space, and then a certain distance can be used to represent the similarity between the sample points. The closer sample points are more similar in nature. On the contrary, the greater the distance between sample points, the greater the difference.

Similarity Measures

Correlation Coefficient Method. The correlation coefficient is a statistical indicator to reflect the degree of the correlation between variables (Ye, 2013). The correlation coefficient is calculated by the product difference method, which is also based on the deviation of the two variables and their respective averages. The two deviations are multiplied to reflect the degree of correlation between the two variables.

$$r_i = \frac{\sum_{i=1}^{n}\left(x_i - \overline{x}_i\right)\left(y_i - \overline{y}_i\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \overline{x}_i\right)^2 \sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)^2}} \tag{6}$$

$$\overline{x}_i = \frac{\sum_{i=1}^{n} x_i}{n} \tag{7}$$

$$\overline{y}_i = \frac{\sum_{i=1}^{n} y_i}{n} \tag{8}$$

Where, r_i is the correlation coefficient value between the two vectors, $\overline{x}_i$ and $\overline{y}_i$ are the average values of the two vectors, respectively. In this research, the two vectors represent each IMF component obtained after EEMD decomposition and the original signal.

Angular Similarity Method.

$$S\left(X_i, X_j\right) = \frac{X_i^T X}{\left\|X_i\right\| \cdot \left\|X_j\right\|} \tag{9}$$

The measure of angle cosine reflects the geometric similarity, which is invariable for the rotation and scaling of the coordinate system, but it is not invariable for displacement and general linear transformation (Ji et al., 2014).

Kullback-Leibler Divergence (KLD) Method. An unknown distribution $p(x)$ is assumed to be modelled with an approximate distribution $q(x)$, and $q(x)$ is used to create an encoding system that passes the value of x to the receiver.

$$KLD(p \| q) = -\int p(x) \ln\left[\frac{q(x)}{p(x)}\right] dx \tag{10}$$

Since $q(x)$ is not the true distribution $p(x)$, the average encoding length will increase compared with the true distribution $p(x)$ for encoding information, the increased information amount is *KLD*, also known as relative entropy (So et al., 2016). Figure 3 shows the three similarity measurement curves of the original signal and each IMF component after the EEMD decomposition.

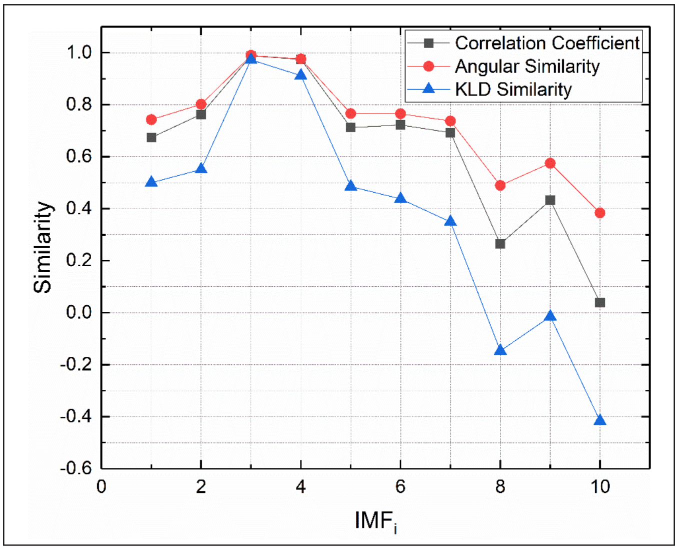

Figure 3. Similarity measures of the original signal and corresponding IMF components

Distance Measures

Euclidean Distance Measure. It is equivalent to the point-to-point distance represented by a vector in a high-dimensional space, which can intuitively represent the similarity between modes. The smaller the distance, the more similar.

$$D(X_i, X_j) = \|X_i - X_j\|_2 \tag{11}$$

Since the dimensions of each component of the feature vector are inconsistent, it is usually necessary to standardize each component, so that it is independent of the unit. For example, Euclidean distance may produce invalid results for two different indexes of height and weight (Siless et al., 2018).

Manhattan Distance Measure. In Manhattan, someone needs to drive from one intersection to another. The driving distance is not a straight line between two points. The actual driving distance is "Manhattan distance". Manhattan distance is also known as the city block distance (Thakur et al., 2019).

$$dis_{man}\left(x,y\right)=\sum_{i=1}^{n}\left|x_i-y_i\right| \tag{12}$$

The above equation represents the Manhattan distance between two points on an n-dimensional plane.

Chebyshev Distance Measure. If there are two vectors or two points p and q, whose coordinates are p_i and q_i, respectively, then the Chebyshev distance between them is defined as follows:

$$D_{Chebyshev}\left(p,q\right)=\max_i\left|p_i-q_i\right| \tag{13}$$

The above formula is also equal to the extreme value of the following L_p metrics:

$$\lim_{k\to\infty}\left(\sum_{i=1}^{n}\left|p_i-q_i\right|^k\right)^{1/k} \tag{14}$$

So Chebyshev distance is also called the L_∞ measure. From a mathematical point of view, Chebyshev distance is a measure derived from a uniform norm, which is also a kind of super-convex metric (Bhunre et al., 2019). The distance measurement between the original signal and each IMF component is shown in Figure 4.

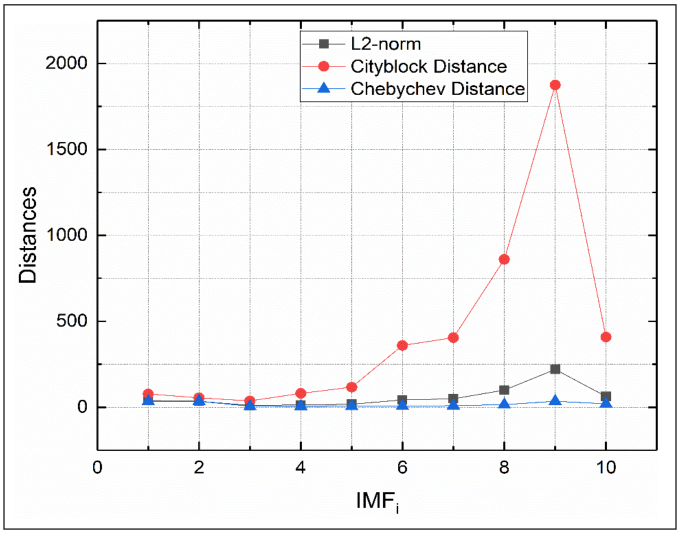

Figure 4. Distance measures of the original signal and corresponding IMF components

Energy-based Adaptive Thresholding

After the EEMD decomposes the noisy signal, the IMF component of each order is obtained. Then, a reasonable threshold is selected for the high-noise IMF component, and the corresponding IMF component is processed by the obtained threshold. Therefore, threshold selection is crucial.

In this research an energy-based adaptive thresholding method inspired by wavelet thresholding is proposed. According to the energy characteristic of each IMF, the method adapts to the special property of each IMF, which breaks the limitation of wavelet fixed threshold, so it can better reduce the noise of the IMF components (Geryes et al., 2019).

The signal $y(t)$ is decomposed by EEMD to obtain IMF components, and some reasonable thresholds are selected for each high-noise IMF component, and these thresholds convert c_i to $\tilde{c}_i$ and then reconstruct the EEMD. The reconstructed signal can be expressed as follows:

$$z(t) = \sum_{i=1}^{M} \tilde{c}_i + \sum_{i=M+1}^{N} c_i + r \tag{15}$$

Where $z(t)$ is the reconstructed signal, $\tilde{c}_i$ is the IMF components requiring threshold processing, and M is the number of IMFs threshold processing. c_i is the unprocessed IMF component, r is the residual component, and N is the total number of IMF components (Kopsinis & McLaughlin, 2009).

The EEMD decomposition is similar to the wavelet transform, and the noise is mainly concentrated in the first component that is decomposed. Thus, in the adaptive threshold noise reduction of EEMD, the estimated noise variance is taken as IMF1. That is, the noise variance is estimated according to the following formula:

$$\sigma = \frac{MAD\left(\left|IMF_1\right|\right)}{0.6745} \tag{16}$$

Where, *MAD* represents the mean absolute deviation, and *IMF1* is the intrinsic mode function of the first layer obtained by EEMD. With respect to the threshold selection, the universal threshold $T{=}\sigma\sqrt{2\ln N}$ is widely used. However, different IMFs have different energy components, which is clearly inappropriate of the fixed threshold noise reduction for different energy IMFs. The energy formula is as follows:

$$E_k = \frac{1}{N}\left(\sum_{i=1}^{N}\left(IMF_{ki}\right)^2\right) \tag{17}$$

Where E_k is the energy of the kth IMF, and N represents the length of the IMF sequence of each order. It turns out that the noise contained in each IMF component is coloured and has different energies. An improved universal threshold is especially important, as follows:

$$T_k = C\sqrt{E_k 2\ln N} \tag{18}$$

Where C is a constant. It can usually be determined through experiments, which can be preliminarily selected as σ.

RESULTS AND DISCUSSION

Noise Reduction Test of The Proposed Method

In order to verify the effectiveness of the proposed noise reduction method, a segment of signal in the actual magnetic eddy current signal database was randomly selected for noise reduction. The signal can be described as in Figure 5.

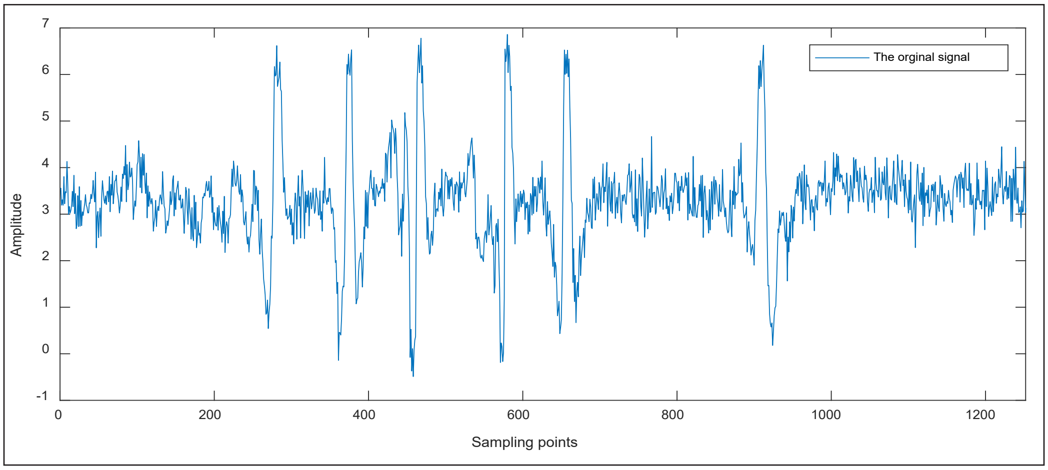

Figure 5. Original defects signal. Signal Y(t) represents an original noisy signal, which includes six irregularly sized corrosion defects.

According to the procedure of the proposed noise reduction method, EEMD decomposition of the noisy signal is carried out to obtain each IMF component (Figure 2). The comparison of probability density function (PDF) of the original signal Y(t) with the corresponding IMFs provides a preliminary and intuitive observation of the similarity between each IMF and the original signal as shown in Figure 6 (Komaty, 2013).

Meanwhile, the similarity measure in Figure 3 shows that the similarity reaches the maximum when IMF=3, and then the similarity gradually decreases. It can be found in Figure 4 that the distance measure increases sharply when IMF=9 and the scale of the probability density function of Figure 6 also confirm the accuracy of the distance measures. Therefore, the number of IMF requiring threshold processing is M=9.

Then, the energy-based adaptive threshold was used to remove the high noise of the selected IMF components. The energy corresponding to each IMF can be obtained from equation 17, so as to obtain the adaptive threshold value. The adaptive threshold can remove the impurity noise of high noise IMFs. According to equation 15, the noise reduction diagram shown in Figure 7 is obtained.

By comparing the signals before and after noise reduction in Figure 5 and Figure 7, it can be found that the proposed noise reduction method can effectively retain the overall shape features of defect signals, laying a foundation for feature extraction and pattern recognition of defect signals later.

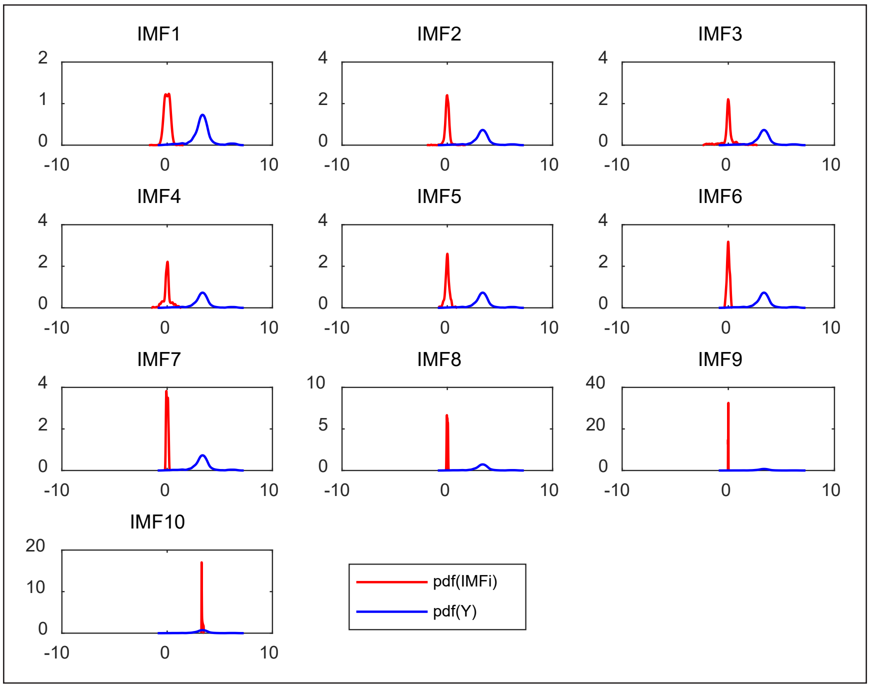

Figure 6. Comparison of PDF of original signal Y(t) and corresponding IMFs

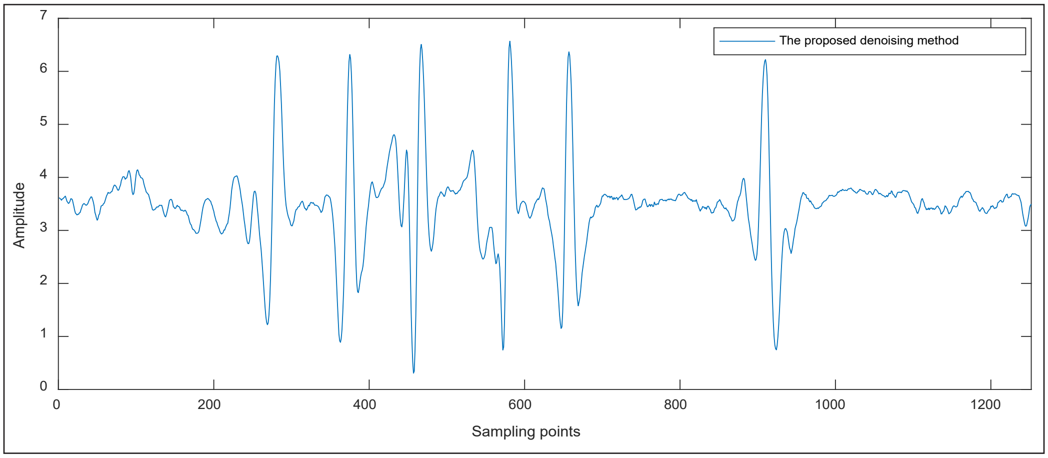

Figure 7. The noise reduction results of the proposed method

Performance Comparison

The proposed noise reduction method was compared with the wavelet soft threshold noise reduction method and wavelet hard threshold noise reduction method. The noise reduction effect of the signal is quantified by signal to noise ratio (SNR), mean square error (MSE) and percent root means square difference (PRD). The expressions of SNR, MSE, and PRD are as follows:

$$SNR = 10\log_{10}\left[\frac{\sum_{j=1}^{N} x^2(j)}{\sum_{j=1}^{N}[x(j)-\hat{x}(j)]^2}\right] \tag{19}$$

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left[x(j)-\hat{x}(j)\right]^2 \tag{20}$$

$$PRD = 100\sqrt{\frac{\sum_{j=1}^{N}\left(x(j)-\hat{x}(j)\right)^2}{\sum_{j=1}^{N}\hat{x}^2(j)}} \tag{21}$$

Where, $x(j)$ is the amplitude of the original signal at the sampling point j. $\hat{x}(j)$ is the amplitude of the denoised signal at position j. N is the length of the signal.

The noise reduction result of wavelet soft threshold method, wavelet hard threshold method and the proposed denoising method in this research were compared, as shown in Figure 7, Figure 8 and Figure 9 respectively. In addition, the comparison of SNR, MSE and PRD before and after signal noise reduction shows that the proposed denoising method in

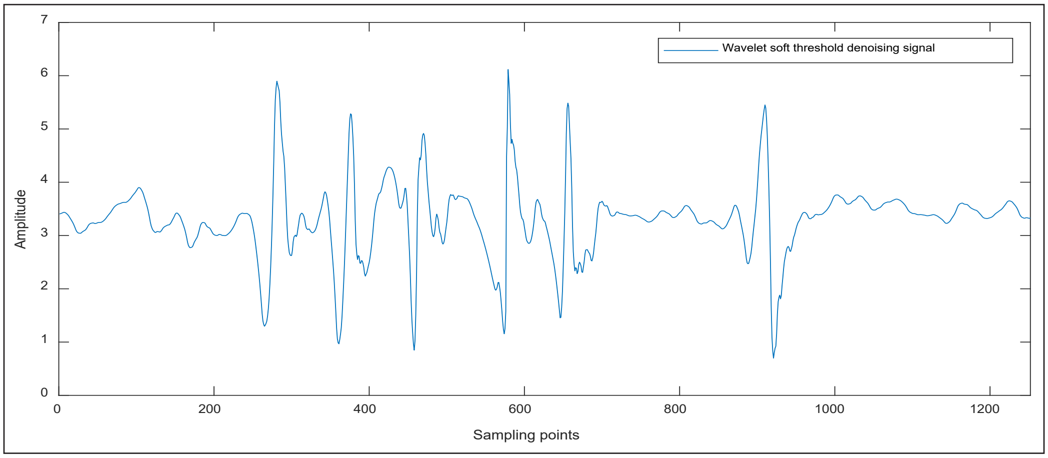

Figure 8. The noise reduction of wavelet soft threshold method

this research can improve the SNR of pipeline magnetic eddy current defect signals and reduce the MSE and PRD of signals as shown in Table 1.

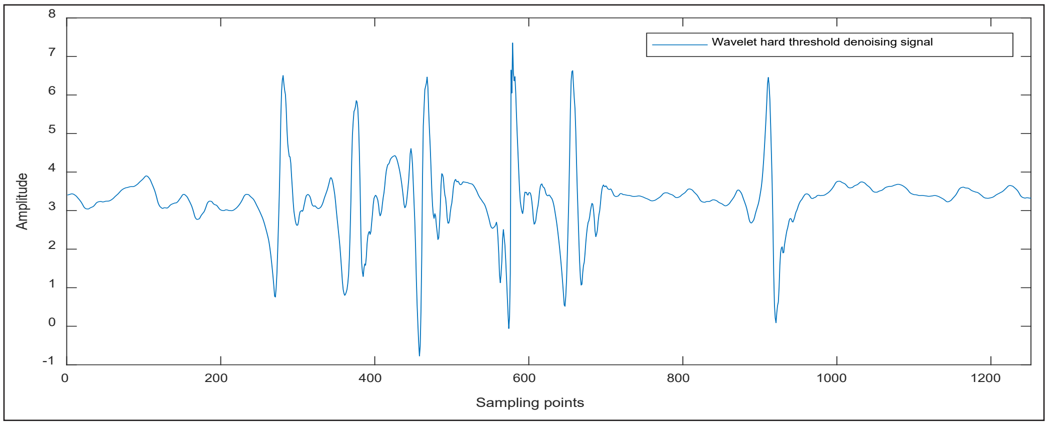

Figure 9. The noise reduction of wavelet hard threshold method

Table 1
SNR, MSE and PRD comparison for noised defect signal

	Wavelet soft threshold method	Wavelet hard threshold method	The proposed method
SNR	15.7443	17.7891	19.1886
MSE	0.3019	0.1932	0.1536
PRD	0.1632	0.1290	0.1098

CONCLUSION

A new adaptive noise reduction method is presented in this research. This method includes EEMD decomposition, PDF visualization comparison, PDF similarity measure comparison, energy-based adaptive thresholding, signal reconstruction. Combined with PDF intuitive comparison and measure analysis of each IMF and the original signal, the boundary value of the high-noise IMF component and low-noise IMF component is more accurately obtained. Among them, the Manhattan distance measure can better identify the boundary than other measures in the measure analysis. At the same time, according to the energy characteristics of each IMF, an adaptive energy-based thresholding method is proposed, and it is superior to wavelet hard threshold denoising method and soft threshold denoising method when it is applied to actual magnetic eddy current signal noise reduction. In fact, the proposed denoising method is also applied to many other magnetic eddy current signals, and the denoising effect is obvious. In addition, the proposed noise reduction method is likely to be used in noise reduction processing of other detection signals, such as the vibration signal of gearbox and compressor.

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