Influence of different wavelet bases and threshold estimation on noise reduction of substation fault signals under different SNR

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Abstract: With the rapid development of power industry, the number of substations is also increasing, and the voltage level is also higher and higher, and the types of equipment are diverse. The detection of equipment fault signal in substation is an important part to ensure the normal operation of electric power. Only timely detection of fault signal and corresponding processing can ensure the overall operation of substation. But the fault signal often contains a lot of white noise, which will interfere with our judgment of the fault point. How to extract the effective signal from the noisy signal becomes particularly important, but under different signal-to-noise ratio, the selection of different wavelet basis and threshold estimation also have a great impact on the noise reduction effect. In this paper, we choose different wavelet bases and threshold estimation under several different signal-to-noise ratios to study their influence on the effect of signal denoising.

1. Introduction
With the progress of society and the development of science and technology, the power system is all over the world, which also leads to the power system structure is more and more huge, and the facilities and equipment are more and more complex. However, in the substation, the equipment is often disturbed by the surrounding environment and prone to failure. Once the failure is not found and handled in time, the residential and industrial power consumption will be greatly affected, which will cause huge losses in human, material and financial resources [1].

In real life, the measured signal will contain a large number of noise signals due to various reasons, which will lead to signal interference in signal fault analysis. Therefore, how to get the effective signal we need from the noisy signal becomes particularly important. Through the analysis of the collected waveform signal, it is found that the main component of noise is white noise or additive noise [2][3][4].

White noise has a wide range of sources, mainly from the shot noise of electronic semiconductor devices in the measurement loop and measurement equipment, the resistance of electronic devices or the thermal noise in the operation of electrical equipment. The frequency of white noise is very wide, almost covering the entire frequency domain. There may be overlap with the partial discharge signals...
of various frequency bands. It is difficult to completely eliminate the influence of white noise interference whether it is measured in the laboratory or measured on the engineering site. Therefore, for the white noise interference The suppression of signal has always been a hot research problem of signal noise reduction.

2. Methods of signal noise reduction

At present, the common methods of fault signal de-noising include the signal de-noising method based on fast Fourier transform, the signal de-noising method based on wavelet transform, and the signal de-noising method based on empirical mode decomposition (EMP).

2.1. Fourier transform

Fourier transform (FT) is a very important application tool in many fields of natural science, especially in signal processing, image processing, quantum physics and other disciplines. Generally, Fourier transform analysis refers to Fourier transform and Fourier series.

From the perspective of modern mathematical analysis, we can see that Fourier transform is a special integral transform. It can express a certain function as the integral form of sine basis function when it meets certain conditions. Continuous Fourier transform and discrete Fourier transform are variants in different research areas.

In the calculation of Fourier transform, the discrete points on the selected domain r need to be calculated. But in practical application, people want to directly analyze the changes and characteristics of the signal, so the signal must be limited, in a certain frequency domain and time domain, the signal is also discrete, so people define it as discrete Fourier transform. In addition, Fourier transform also has the following properties: linear property, displacement property, frequency shift property, convolution theorem, symmetry property, energy integral property.

2.2. Basic concepts of wavelet transform

Wavelet analysis is a subject based on Fourier transform, and it provides new ideas and new solutions for many fields, which is very popular in scientific research. Wavelet analysis is not only a very rich and reasonable mathematical method, but also a special tool which plays a key role in engineering practice.

From a mathematical point of view, wavelet can be defined as a new field of localization for a given function. Generally speaking, wavelet transform has better window characteristics.

2.3. Wavelet denoising

Because wavelet denoising method is suitable for both stable and unstable signals, it is often used as a good means of signal denoising. Wavelet transform was first proposed by J. Morlet. After years of development, wavelet transform is widely used in all kinds of signal denoising with its advantages of multi-resolution analysis. Many researches at home and abroad show that wavelet denoising method can effectively suppress white noise interference. At present, the widely used signal denoising methods based on wavelet transform can be divided into Mallat et al's signal denoising method based on wavelet modulus maximum, Stanford University Donoho et al's signal denoising method based on wavelet domain threshold, because the modulus maxima method needs to use the maximum layer modulus maxima to find the modulus maxima of other layers, the process is very complicated, but the wavelet threshold denoising process is relatively simple. Wavelet threshold method is used to analyze traveling wave fault signal in transmission line.

The core of wavelet denoising method is based on the different properties of signal and noise, that is to say, the signal part and noise are distributed in different areas.

The frequency range has different characteristics. The correlation coefficient related to noise in frequency domain is set to 0, and the useful signal is kept intact. Finally, the original signal is reconstructed by wavelet reconstruction.
2.4. Selection of wavelet basis
An ideal wavelet should have the following characteristics:

1) Orthogonality; 2) Tightness; 3) Symmetry. 4) Regularity; 5) High-order vanishing moment.

2.5. Selection of threshold estimation
At present, the commonly used threshold estimation method is heursure threshold method [23], rigrsure threshold method [24], minimaxi threshold method [25], visushrink threshold method [26]. However, because the visushrink threshold method is limited by the length of the signal, when the signal is too long, some signals will be erased, so this method is not discussed.

2.6. Selection of threshold
Wavelet de-noising uses soft threshold to quantify wavelet coefficients, because the hard threshold function is easy to cause signal jitter, and soft threshold can make the de-noising result smoother, but it will reduce the clarity of the result, so soft threshold is generally selected in fault signal detection.

2.7. Selection of decomposition layers
In the noise reduction of fault signal, the number of decomposition layers is generally the middle one. In this paper, five decomposition layers are selected. Denoising effect of three kinds of common wavelets on noisy signals with different redundancy.

3. The effect of several common wavelet on noise reduction of signal with different redundancy
In this chapter, the original fault signal is added with different decibels of white noise to make the noise content of the signal different, and then several commonly used wavelet bases: Haar wavelet, DB6 wavelet, Sym8 wavelet, coif4 wavelet, bior5.5 wavelet are used to denoise the noisy signals under different SNR, and the denoising effect is compared.

Use matlab to load an original fault signal, as shown in Figure 1:

![Original fault signal](image1)

**Figure 1.** Original fault signal

Gaussian white noise with signal-to-noise ratio of 7dB, 8dB, 9dB and 10dB is added to the original signal respectively to obtain the signal as shown in the figure below:

![Denoised signal with signal-to-noise ratio of 7dB](image2)
![Denoised signal with signal-to-noise ratio of 8dB](image3)

**Figure 2.** Denoised signal with signal-to-noise ratio of 7dB

**Figure 3.** Denoised signal with signal-to-noise ratio of 8dB
Figure 4. Denoised signal with signal-to-noise ratio of 9dB

Figure 5. Denoised signal with signal-to-noise ratio of 10dB

The following is a noise signal with a signal-to-noise ratio of about 7dB. Different wavelets are used to denoise the noise signal by selecting 5-layer decomposition, soft threshold function and heursure threshold estimation. The de-noising results are shown in the figure below:

Figure 6. Signal after haar wavelet denoised

Figure 7. Signal after wavelet denoising of db6

Figure 8. Signal after wavelet denoising of sym8

Figure 9. bior5.5 Wavelet denoised signal

Figure 10. coif4 wavelet denoised signal

It can be seen from the denoising effect of the above wavelets that the denoising effect of several wavelets is not obvious for the signal-to-noise ratio of 7, and most of them appear singular points. Although the bior5.5 wavelet appears singular points, the position of the singular points is not consistent with the original signal, so these wavelets can not denoise the signal-to-noise ratio of 7 very well.

The following is to use different wavelets, 5-layer decomposition, soft threshold function and heursure threshold estimation to denoise the noisy signal with a signal-to-noise ratio of about 8dB. The denoising results are shown in the following figure:
From the denoising effect of the above wavelets, we can see that DB6, Sym8, biort5.5 wavelets can denoise the noisy signal with SNR of 8, in which DB6 will save more useful information of the original signal, Sym8, biort5.5 will be relatively less, Haar wavelet and coif4 wavelet can not denoise the noisy signal.

For the noisy signal with a signal-to-noise ratio of about 9dB, different wavelets are used to denoise the noisy signal by selecting 5-layer decomposition, soft threshold function and heursure threshold estimation. The denoising results are shown in the figure below:
From the denoising effect of the above wavelets, we can see that Haar, DB6, Sym8, bior5.5, coif4 wavelets can denoise the noisy signal with SNR of 9, and Haar, Sym8, bior5.5 save more useful information of the original signal than the other two wavelets.

The following is to add noise with signal-to-noise ratio of about 10dB to the original signal, respectively use different wavelets, select 5-layer decomposition, soft threshold function, heursure threshold estimation to denoise the noisy signal, and get the following results:

From the denoising effect of the above wavelets, we can see that Haar, DB6, Sym8, bior5.5 and coif4 wavelets can denoise the noisy signal with SNR of 10, and Haar and Sym8 have more useful information for signals.

From the above analysis, we can draw the following conclusions: DB6 wavelet has better denoising ability when the signal-to-noise ratio is low (such as 8dB), but when the signal-to-noise ratio reaches a certain degree (such as 9dB or 10dB). Haar wavelet and Sym8 wavelet can retain more useful information for signals.

### 4. Denoising effect of 4-threshold estimation on noisy signals with different redundancy

According to the conclusion in the third chapter, DB6 wavelet is selected when the signal-to-noise ratio is 8dB, and different threshold estimation is used to denoise the noisy signal respectively, and the most appropriate threshold estimation is selected by comparing the denoising effect; Haar wavelet and
Sym8 wavelet are selected when the signal-to-noise ratio is 9dB and 10dB, and different threshold estimation is used to denoise the noisy signal respectively, and the denoising effect is compared, and the most appropriate threshold estimation is selected. The results are as follows:

The figure below shows that DB6 wavelet is selected when the signal-to-noise ratio is 8dB, and different threshold estimation is used to denoise the noisy signal.

![Figure 26. Selects DB6 wavelet and heursure threshold to estimate the denoised signal](image)

![Figure 27. Signal after wavelet denoising of db6](image)

![Figure 28. Selects db6 wavelet and Minimaxi](image)

It can be found from the above figure that DB6 wavelet and heursure threshold estimation have the best denoising effect when the signal-to-noise ratio is 8.

The figure below shows that when the signal-to-noise ratio is 9dB, Harr wavelet and Sym8 wavelet are selected to denoise the noisy signal with different threshold estimation.

![Figure 29. Haar wavelet and heursure thresholds estimate the denoised signal](image)

![Figure 30. Haar wavelet and Rigrsure thresholds estimate the denoised signal](image)

![Figure 31. Haar wavelet and Minimaxi threshold estimation of signal after noise](image)

![Figure 32. Sym8 wavelet and heursure thresholds estimate the signal after noise reduction](image)
Figure 33. Wavelet and Minimaxi threshold estimation of signal after noise reduction

Figure 34. Signal after noise reduction is estimated by wavelet and Rigsure thresholds of Sym8

It can be found from the above figure that Haar wavelet and Sym8 wavelet have the best denoising effect respectively with heursure threshold estimation when the signal-to-noise ratio is 9.

The figure below shows that when the signal-to-noise ratio is 10dB, Harr wavelet and Sym8 wavelet are selected to denoise the noisy signal with different threshold estimation:

Figure 35. Haar and heursure thresholds estimate the signal after wavelet denoising

Figure 36. Haar and Rigsure thresholds estimate the signal after wavelet denoising

Figure 37. Haar and Minimaxi thresholds estimate the signal after wavelet noise reduction

Figure 38. Sym8 wavelet and heursure thresholds estimate the signal after noise reduction

Figure 39. Sym8 and Rigsure thresholds estimate the signal after wavelet denoising

Figure 40. Signal after wavelet noise reduction is estimated by minimaxi threshold

It can be found from the above figure that when the signal-to-noise ratio is 10, Haar wavelet and Sym8 wavelet have the best denoising effect compared with heursure threshold estimation respectively.

5. Conclusion

From the above analysis, we can get the following conclusions: when the signal-to-noise ratio is too low, the noise signal completely submerges the effective signal, and the wavelet de-noising method...
can not be used for de-noising; when the signal-to-noise ratio is low (such as 8dB), DB6 wavelet and heursure threshold estimation have better de-noising ability; when the signal-to-noise ratio reaches a certain degree (such as 9dB or 10dB). Haar wavelet is selected Compared with Sym8 wavelet and heursure threshold estimation, it can better retain the useful information of the signal.

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