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Research Article

Identification of Contact Relationship of Electrical Engineering Distribution Network with Two-Dimensional Wavelet Threshold Deep Neural Network

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With the improvement of electrification in power systems, accurate and rapid fault location helps to repair faults, which is of great significance to the stability of distribution network operation. As an important part of power distribution in the power system, the electrical engineering distribution network is directly connected to the power transmission system and power end users. Its safety and reliability are related not only to the power sales interests of power companies, but also to the power users' rights and interests in power consumption. In this paper, an improved threshold based on the peak-sum ratio (PSR) is proposed, the time-frequency features in the disturbance signal are extracted through the continuous transformation of the two-dimensional wavelet threshold deep neural network to generate the disturbance time-frequency map of the electrical engineering distribution network, and then the deep learning model is used to analyze the model. After the classification performance is continuously optimized, the signal disturbance identification of electrical engineering distribution network is realized. By calculating the PSR of the distribution network, the correction factor can adaptively adjust the general threshold according to the noise distribution characteristics of different disturbance signals. By analyzing the data one by one, it can be seen that the improved threshold function has obvious advantages in the input signal-to-noise ratio of 10–12 dB, 16–18 dB, and 21–26 dB. At 13 dB, 14 dB, 20 dB, 27 dB, and 28 dB, the SNR difference of the distribution network is very small, and at 15 dB, 19 dB, 29 dB, and 30 dB, it is slightly inferior, but its denoising effect is generally better. The example results have shown that the recognition accuracy of the two-dimensional wavelet threshold denoising method in a noise-free environment has been effectively improved, and it has a certain anti-noise performance. The method proposed in this study has few feature extraction steps, is easy to implement, and is suitable for more types of disturbances.

1. Introduction

Considering that nearly 90% of power system outages originate from the distribution network, quickly providing accurate fault location information can help power operators to speed up the system repair process, thereby reducing operating costs. Therefore, the identification of distribution network fault location has been a research hotspot in the past two decades. With the accelerated development of industrial technology, the degree of electrical dependence is also increasing. At the same time, many new electrical equipment connected to the power grid will cause various electromagnetic interferences to the power system. This is also a potential hidden danger that the power system cannot operate safely, which makes the reliable operation of the distribution network attract the continuous attention of the majority of researchers. Therefore, an extremely important research topic of distribution network is fault location research.

The fault and protection devices of the traditional distribution network also need to adapt to the protection of the distribution network under the new situation, and it is more and more urgent to propose new methods and methods for fault protection. Emhemed A A S believed that LVDC has the potential to support distributed renewable energy [1]. The distribution network is responsible for distributing electrical energy at the transmission terminals. Its safe and stable operation is of great significance. Takahashi thereby took advantage of the router's integrated storage capacity [2]. Jie considered an integrated distribution network design problem in which all retailers are faced with uncertain demand. The goal is to minimize the expected total cost due to distribution center location, transportation, and inventory. The first stage decides which retailers to choose as DCs, and the second stage deals with the cost of DC retailer distribution, shipping, and inventory. A similar model requires that all retailers have demand in each case to have their variance proportional to their mean [3]. Anna believed congestion management [4]. Wang believes have attracted extensive attention [5]. They are not very good for fault detection of distribution network. For this reason, this paper retrieves relevant materials and optimizes the performance of distribution network by exploring the change of two-dimensional wavelet threshold.

After the load data are processed by the two-dimensional wavelet threshold denoising method, it can have obvious prediction accuracy. Jayakumar EP described an FPGA implementation of a pseudorandom bit sequence generator (PBSG) based on elliptic curves over GF (2 m). He proposed a new scalable multiplier structure to implement elliptic curve coprocessors, which was used to implement PBSG [6]. Wang proposed a new hybrid method [7]. Spoorthi GE considers phase unwrapping [8]. Khorsheed OK believed that over the past few years, modern image processing technology has pervaded all aspects of his life. Observers can notice that information security, medical diagnosis, military communications, etc., and all rely on image processing techniques [9]. Li believed the denoising of the VPVS [10]. Furthermore, 2D wavelet thresholded deep neural network denoising can improve data quality. Two-dimensional wavelet thresholding deep neural network can change the resolution of two-dimensional wavelet thresholding.

From the definition of active distribution network, it can be known that based on intelligent measurement technology and information communication technology, active distribution network in this paper can manage all kinds of electricity demand, thereby improving the flexibility of the power grid and better meeting the electricity demand of users. This study presents the related principles of improved thresholds and threshold functions. At the same time, the current fault location methods of distribution network are sorted and summarized. The fault location methods include the part of fault-type identification and the part of fault distance calculation, and their basic principles and specific methods are expounded in detail. In this paper, an adjustable threshold function is constructed, and it has the advantages of both soft and hard threshold functions by adjusting the parameters. The EMD analysis of the distribution network voltage signal shows that the disturbance time is 0.0599 s–0.1602 s during the disturbance time 0.06 s–0.16 s, which is consistent with the time set in the study. The average value of the signal amplitude is 0.4005 V. And the largest peaks at the time of disturbance in the study appeared at points 614 and 1640, respectively.

2. Identification Method of Contact Relationship of Electrical Engineering Distribution Network

2.1. Electrical Engineering Distribution Network. The synchrophasor measurement technology in the electrical engineering distribution network is relatively backward, the main reason is that the development of the traditional electrical engineering distribution network is not complete, and there is less power information to be monitored. But with the development of high and new technology, the state of electrical engineering distribution network has been significantly different from before. In recent years, many universities have carried out long-term project research on synchrophasor measurement devices. Its measurement error is small, and the sampling frequency of the cycle wave is high, which satisfies the needs of fast and accurate fault location in the electrical engineering distribution network and has a good application prospect.

The operation state of the power distribution system directly affects the national production and economic construction. Once a fault occurs, it will cause power outages to users, affecting the normal operation of enterprises and people's daily life. In China's power distribution system, the load fluctuation is very random, the structure is complex, its failure rate can be as high as 80%, and it mostly occurs in inaccessible mountainous areas. When a single-phase grounding fault occurs in the distribution line, due to the limitation of geographical factors, the fault line is not easy to check, and the fault location is not easy to find. Therefore, the power operation and maintenance department and fault removal technology need to be further improved. In China's power distribution system, in order to avoid the arc problem caused by the grounding current, the neutral point of the three-phase four-wire system is mostly grounded by the arc suppression coil.

The use of a large number of shock and nonlinear power electronic devices and the vigorous promotion of new energy grid-connected technologies have made the complexity of power system loads increase rapidly, which in turn caused various transient and steady-state power quality problems. For example, in the field of new energy power generation such as wind energy, photovoltaics, and biomass power, wind power generation has strong volatility and intermittent due to the operating power characteristics of its own wind turbines and the uncertainty of wind energy resources in nature. When the short-circuit ratio of the fan access point is too large, it will cause voltage fluctuation and flicker, resulting in a large deviation between the voltage waveform and the actual power frequency voltage. Photovoltaic power generation has large-scale integration of power electronic technologies such as photovoltaic modules, inverters, and controllers. in the electrical engineering distribution network based on photovoltaic systems, which causes a large number of high-frequency harmonics to be injected into the power grid to cause resonance, resulting in excessive transient voltage damage to electronic equipment. In severe cases, large-scale power outages may occur.

2.2. Two-Dimensional Wavelet Thresholding Deep Neural Network. The two-dimensional wavelet threshold deep neural network can effectively reduce the training data sample size of the electrical engineering distribution network supervision model, avoid the retraining of historical data with large cardinality, and speed up the training speed of the electrical engineering distribution network supervision model. Two-dimensional wavelet thresholding deep neural network theory is part of analytical mathematics. Two-dimensional wavelet threshold deep neural network theory shows great vitality and broad application prospects.

Let the Fourier transform be $\varphi(W)$, when electrical engineering distribution network $\varphi(W)$ satisfies the allowable condition [11]:

$$C_{\varphi} = \int \frac{\varphi(W)}{W} dw < \infty. \tag{1}$$

For the electrical engineering distribution network continuous case, the wavelet sequence is $\varphi(W)_{a,b}$:

$$\varphi(W)_{a,b} = \frac{\varphi(W)}{W} \frac{\varphi(b/a)}{c}. \tag{2}$$

The electrical engineering distribution network undergoes wavelet transform $W_{a,b}$ as [12]

$$\begin{aligned} W_{a,b} &= < f, \\ \psi > &= |a| \int f(t) dt. \end{aligned} \tag{3}$$

Electrical engineering distribution network inverse transformation is

$$f(t) = \frac{1}{c} \int \int_a^1 w(a,b) da\ db. \tag{4}$$

After the DWT decomposition, the electrical engineering distribution network will get a two-dimensional array. Let the scale function be

$$A < \sum \psi(W) < B. \tag{5}$$

$\psi(t)$ is a binary wavelet. If $A = B$, then the above stability condition is called the most stable condition. Among them [13],

$$\begin{aligned} wf(k) &= f(t), \\ \psi(k) &= 2^{-j/2} \int f(t) dt, \\ f(t) &= \sum wf(k)\psi(t) \\ &= \sum wf(k)\psi(t) \int (2t - k) dk. \end{aligned} \tag{6}$$

The wavelet packet analysis, which is further extended from the wavelet analysis, can find the regularities in the detailed information of each scale and screen them out, so that the signal can be divided into more detail.

WPA can be used for frequency tracking, harmonic detection, short-term load prediction, line fault location, online monitoring, fault line selection, etc. [14].

Power Quality Disturbance Signal Denoising Based on Improved Threshold and Threshold Function: In order to improve power quality and ensure the safety and stability of power system operation, it is necessary to conduct in-depth research on power quality. At present, most of the research hotspots on power quality lie in the fields of power quality disturbance signal denoising, identification, and classification. Due to the many types of power quality disturbance signals in distribution network, and the possibility of multiple disturbances occurring at the same time, the components of disturbance signals are more complex, and the difficulty of classification and identification of disturbance signals is aggravated. Therefore, how to realize the accurate identification of the power quality disturbance signal is of great significance to the subsequent power quality management when the noise interference is considered.

The key information containing disturbance characteristics will be confused with noise in the process of signal acquisition and transmission, which affects the accurate detection. In the actual power grid environment, the power quality signal will affect the disturbance type and degree of disturbance. In the general signal denoising algorithm, the denoised signal obtains a higher SNR and a lower RMSE to evaluate the noise removal effect. However, especially for signals with complex frequency components such as harmonics, oscillations, and complex disturbances containing harmonics, the disturbance points are easily removed as noise, which is not conducive to subsequent analysis and detection.

Principle of Two-Dimensional Wavelet Threshold Denoising: This paper uses the current hot two-dimensional wavelet thresholding deep neural network to explore the identification of power quality disturbance signals in noise interference and noise-free environments. It conducts research work on reducing the interference of noise on perturbed features, improving the effectiveness of features, and optimizing the network structure of deep learning models. In the noise interference environment, the traditional wavelet threshold denoising algorithm has shortcomings in threshold setting and threshold function construction, which affects the denoising effect of signal processing. This paper proposes an improved wavelet threshold denoising algorithm, through the improvement of wavelet threshold and threshold function. Its purpose is to improve the denoising effect of the disturbance signal under noise interference, and to better retain the feature information in the original disturbance signal. Through improvement, the new method can be applied to noise interference of different strengths and is suitable for more types of power quality disturbance signals.

The main advantage of two-dimensional wavelet thresholding deep neural network is multi-resolution analysis, that is, multi-scale analysis of the signal according to the time resolution from high to low. The analysis results of the two-dimensional wavelet threshold for the signal not only show the overall change of the signal, but also analyze the local characteristics of the signal pertinently. When analyzing a signal using two-dimensional wavelet thresholding, boundary distortion and noise interference occur: first of all, it is necessary to pay attention to taking measures to perform boundary processing on the improved threshold and the coefficients decomposed by the threshold function to prevent the reconstruction of waveform distortion caused by this problem; secondly, in order to ensure two-dimensional wavelet thresholding deep neural network analysis results, the distribution network signal performs denoising processing [15]. When it is decomposed by wavelet, the energy of useful signal will be concentrated on larger coefficients, while the energy of noise will be distributed on smaller coefficients.

$$x(t) = h(t) + \vartheta(t). \tag{7}$$

In the formula, $h(t)$ is the original signal; $\vartheta(t)$ is Gaussian white noise; and x(t) is the noisy signal. At this time, the inverse discrete wavelet transform (IDWT) of the signal is

$$\int x(t)\vartheta\, d(t) = \int h(t)\vartheta\, d(t) + \int \beta(t)\vartheta\, d(t). \tag{8}$$

In the formula, $\int h(t)$ is the discretized wavelet scaling function.

$$d_{j,k} = U_{j,k} + Ej, k. \tag{9}$$

In the formula, $d_{j,k}$ is the parameter value after the transformation of the noisy signal x (t). The variance and amplitude of white noise decrease when the wavelet transform scale increases, while the original signal does not. When the data are input in the next stage, the data information recorded by the weight W needs to be considered. Through the continuous incoming of data, the information in the hidden layer is continuously updated.

When wavelet decomposition is performed on the noisy signal x (t), the variance and amplitude of the white noise will decrease with the increase of the wavelet transform scale, while the variance and amplitude of the original signal f (t) do not follow the wavelet scale.

Two-dimensional wavelet thresholding can decompose the signal into different scales. When used for feature extraction, features can be extracted at different resolutions to make the characteristics of different types of signals more obvious, which is beneficial to the identification and classification of signals. The hard threshold function is

$$Y_{j,k} = d'_{j,k}. \tag{10}$$

The electrical engineering distribution network soft threshold function is

$$d = \operatorname{sgn}(d - \beta). \tag{11}$$

Among them,

$$\lambda = \sqrt{2N\vartheta}. \tag{12}$$

N is the electrical engineering distribution network signal length.

3. Improved Threshold Denoising Algorithm

3.1. Adaptive Student Threshold. The threshold represents the boundary between noise and useful signal in the wavelet detail coefficients. In the power system, the ideal power supply should provide users with a constant frequency of 50 Hz and sine wave power according to the demand voltage on the power side. However, due to the influence of internal and external factors on the actual power grid, the amplitude, waveform, frequency, and other characteristics of electric energy deviate, which affects the use of users. In order to improve the power grid environment and power supply quality, it is necessary to conduct in-depth research on various types of power quality problems to find out the causes and countermeasures. Wavelet transform can adjust the window function according to the signal frequency, has good local time-frequency characteristics, is suitable for the analysis of changing signals, and is widely used in denoising, singularity detection, and feature extraction of power quality disturbance signals. The general threshold can be corrected by PSR. PSR is a waveform measurement parameter.

The peak-sum ratio can be expressed as

$$\mathrm{PSR} = \frac{\max\left(d_{j,k}\right)}{\sum\left|d_{j,k}\right|}. \tag{13}$$

Electrical engineering distribution network threshold correction factor *Fj* is

$$F_j = L_j^{\mathrm{PSR}}. \tag{14}$$

Among them, L_j is the electrical engineering distribution network length of the input signal. The 1D DWT of layer i is decomposed as

$$\lambda_i = \frac{\varphi\sqrt{2\ln N}}{\lg j}. \tag{15}$$

σ is the electrical engineering distribution network noise standard deviation:

$$\sigma = M\left(\left|\sum_{i=0}^{n} d_{j,k}\right|\right). \tag{16}$$

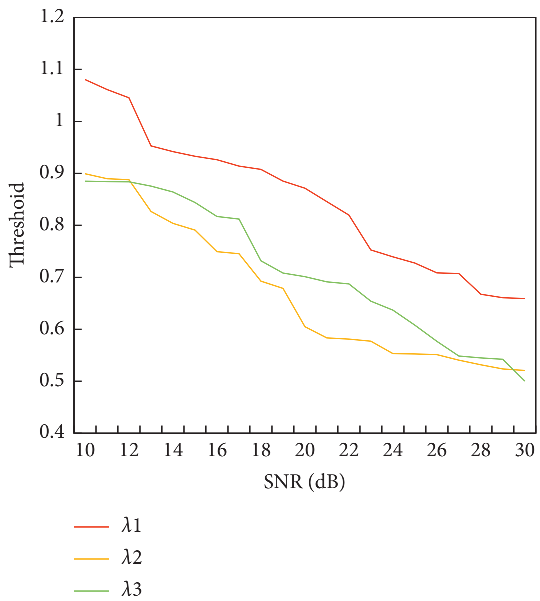
By constructing orthogonal wavelets, the redundant information of each component during wavelet decomposition is avoided, and the amount of calculation is greatly reduced to interrupt signals generated randomly by voltage.

When the SNR of the test signal is 10–30 dB, 5-layer wavelet decomposition is performed on it, and the variation trend of some thresholds with noise is shown in Table 1.

When the SNR is small, it means that it contains more noise. The adaptive two-dimensional wavelet thresholding proposed in this paper decreases with the increase of SNR, indicating that when the signal contains more noise (i.e., with a smaller SNR), the threshold becomes larger and more noise can be removed ((λ_1–λ_3 as shown in Figure 1(a)). When the signal contains less noise (i.e., it has a larger SNR), the threshold becomes smaller, which can effectively prevent the loss of information while removing the noise. The vertical comparison of the threshold value of each layer shows that as the number of decomposition layers increases, the threshold value decreases. The actual noise content is resized (λ_4–λ_5 as shown in Figure 1(b)).

Table 1: Trends of some thresholds with noise.

SNR/dB	10	12	14	16
λ_1	1.083	0.870	0.685	0.539
λ_2	0.673	0.559	0.435	0.539
λ_3	0.513	0.411	0.530	0.353
λ_4	0.436	0.547	0.368	0.310



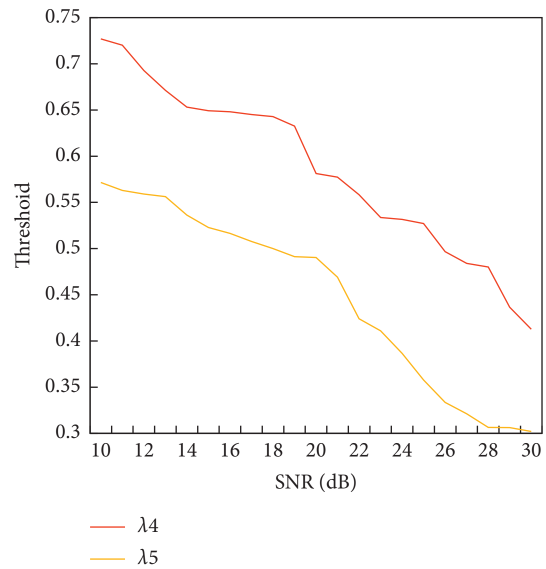


Figure 1: Some thresholds as a function of noise. (a) λ_1–λ_3. (b) λ_4–λ_5.

3.2. Improve the Threshold Function. The improved algorithm flow is shown in Figure 2. The threshold function of soft and hard characteristics is adjusted as

$$d_1 = d_{j,k} - \frac{\lambda}{2e^{-((d-\lambda)/a)}} - \frac{\lambda}{2e},$$
$$d_2 = d_{j,k} + \frac{\lambda}{2e^{-((d+\lambda)/a)}} + \frac{\lambda}{2e^{-(1/a)}}. \quad (17)$$

In the formula, a is any positive constant. The power grid environment is complex and changeable, and different influencing factors will cause different power quality disturbance phenomena. According to the type of disturbance, the cause of the problem can be found out, and the solution can be proposed more efficiently. Therefore, classifying power quality disturbances according to their electromagnetic characteristics is beneficial to the systematic analysis and effective management of power quality problems. Wavelet denoising is as follows: (1) discrete wavelet decomposition of noisy signals and (2) detail part threshold quantization processing.

Power Load Data Denoising Process: To sum up, the basic steps of denoising two-dimensional wavelet thresholding deep neural network in electrical engineering distribution network are as follows:

Step 1. Select the data samples to be predicted to form a two-dimensional data set.

Step 2. Normalize the two-dimensional data set to form two-dimensional grayscale image matrix data.

Step 3. Perform wavelet decomposition on the two-dimensional image signal. A suitable wavelet base is selected for the original noisy image signal f (k), and a set of wavelet coefficients are obtained.

Step 4. Threshold the decomposed wavelet coefficients.

Step 5. Two-dimensional wavelet reconstructs the image signal. The obtained reconstructed signal f(k) is the denoised signal.

Step 6. De-normalize the reconstructed denoised signal f (k). According to the above steps, the power load data denoising process is shown in Figure 3.

Calculate the shortest distance between each data point and other data points of electrical engineering distribution network:

$$d = \min\left(\left|z_{\max} - z_{\min}\right|^2\right). \quad (18)$$

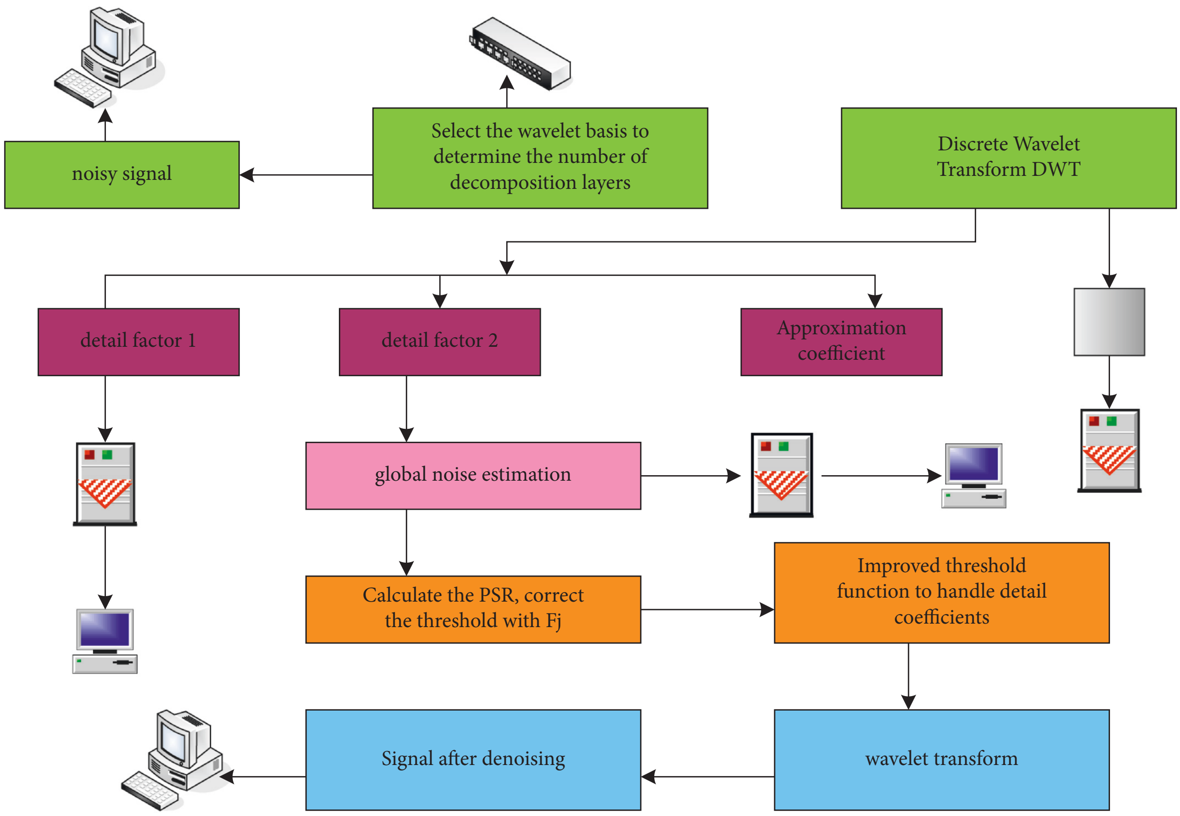


Figure 2: Improved algorithm flow.

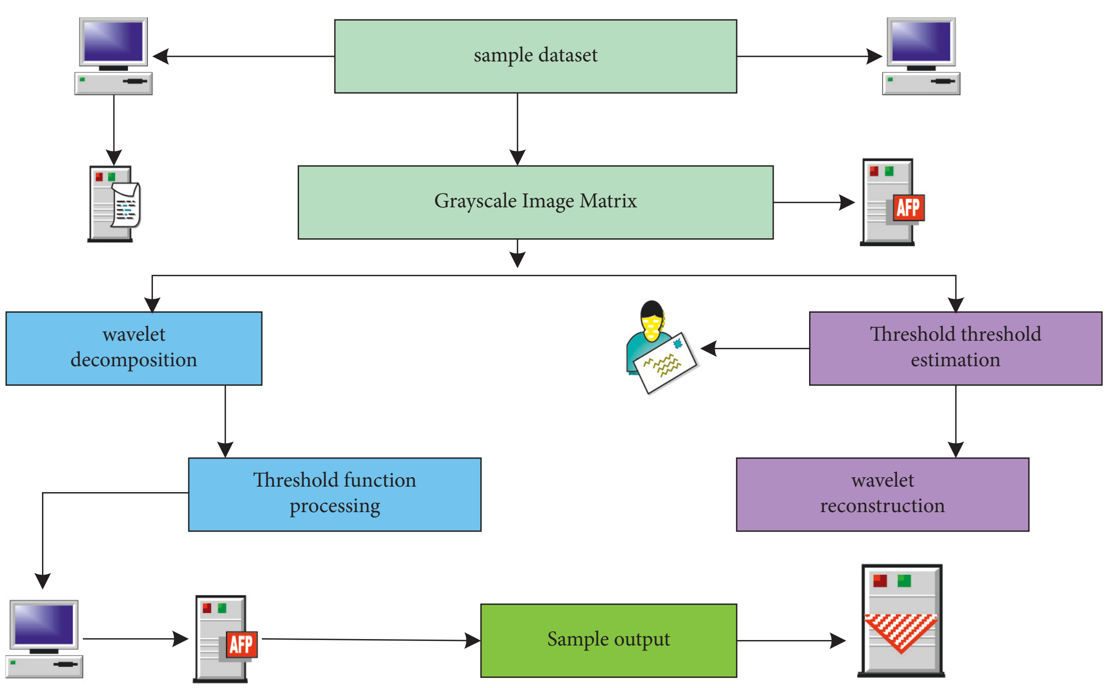


Figure 3: Power load data denoising process.

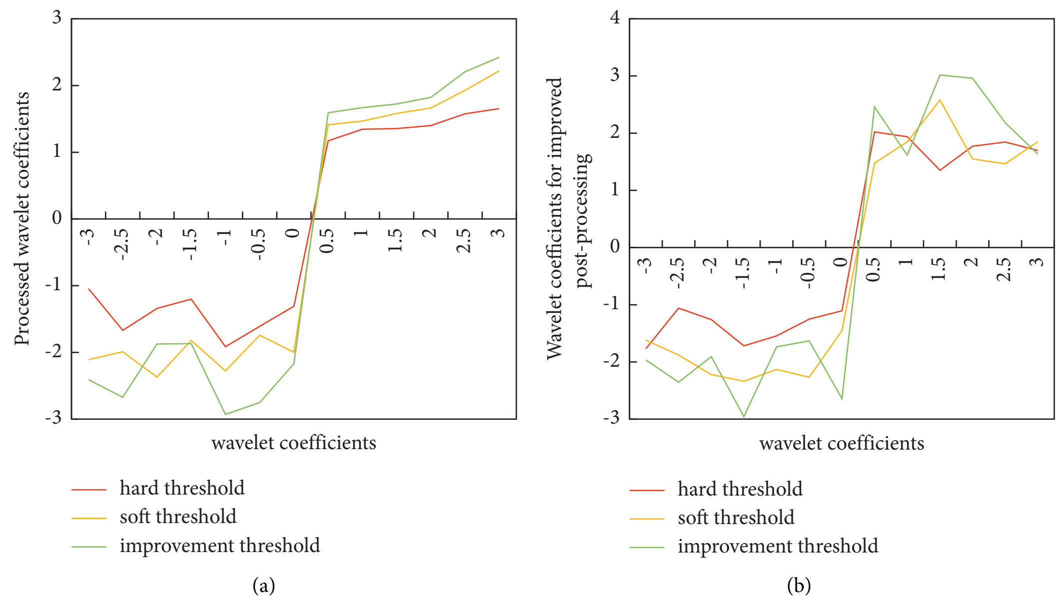


Figure 4: Threshold comparison. (a) Comparison of the characteristics of the improved threshold function with traditional hard and soft threshold functions. (b) The improved threshold function when a takes 0, 1, 2, 5, and 20.

4. Identification Results of Electrical Engineering Distribution Network Liaison Relationship

When the value of parameter a is larger, the change trend of the threshold function is closer, and the denoising effect is more similar (the characteristics of the improved threshold function and the traditional hard and soft threshold functions are shown in Figure 4(a)). When $a = 0$, the improved threshold function coincides with the hard threshold function (the improved threshold function when a is 0, 1, 2, 5, and 20 is shown in Figure 4(b)).

The comparison of the denoising performance of the threshold function is shown in Figure 5. In the case of the same threshold, for the transient oscillation signal, analyzing the data one by one shows that the improved threshold function has obvious advantages in the input signal-to-noise ratio of 10–12 dB, 16–18 dB, and 21–26 dB. The SNR obtained at 13 dB, 14 dB, 20 dB, 27 dB, and 28 dB is roughly the same and slightly inferior at 15 dB, 19 dB, 29 dB, and 30 dB, but its denoising effect is generally better than that of the hard threshold function.

For transient signals such as interruptions, pulses, and oscillations, when the noise intensity is large, the SNR results after denoising are relatively close, and the two-dimensional wavelet has a slight advantage. As the noise intensity changes, the 2D wavelet shows a stable and obvious advantage (the voltage interruption test is shown in Figure 6(a)). Two-dimensional wavelet threshold deep neural network can achieve good denoising effect for transient, steady state and compound disturbance type power quality signals, especially for disturbance signals with harmonic components; the advantage of denoising effect is more significant. The two-dimensional wavelet threshold deep neural network is suitable for a wide range of noise, and the overall performance is stable (the transient impulse test is shown in Figure 6(b)).

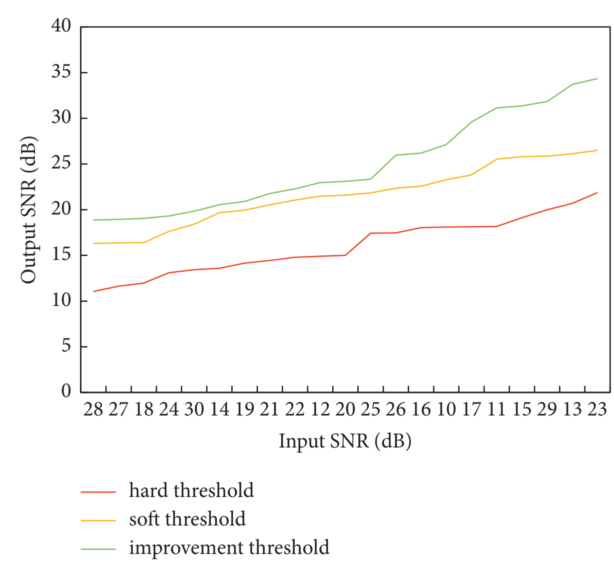


Figure 5: Threshold function denoising performance comparison.

The experimental data in this study are 15 kinds of power quality disturbance time-frequency data sets of electrical engineering distribution network, and each disturbance has 1000 groups, a total of 15000 groups. Based on the experimental process in 7, each disturbance time-frequency map data set is divided according to the ratio of 6 : 2:2, and 600 groups of training sets, 200 groups of verification sets, and 200 groups of test sets are generated as the data input of the experiment. In this paper, the training set is used to train the model, the network parameter loss curve of the fine-tuning model in the validation set tends to converge stably within the first 200 iterations, and the error continues to decrease.

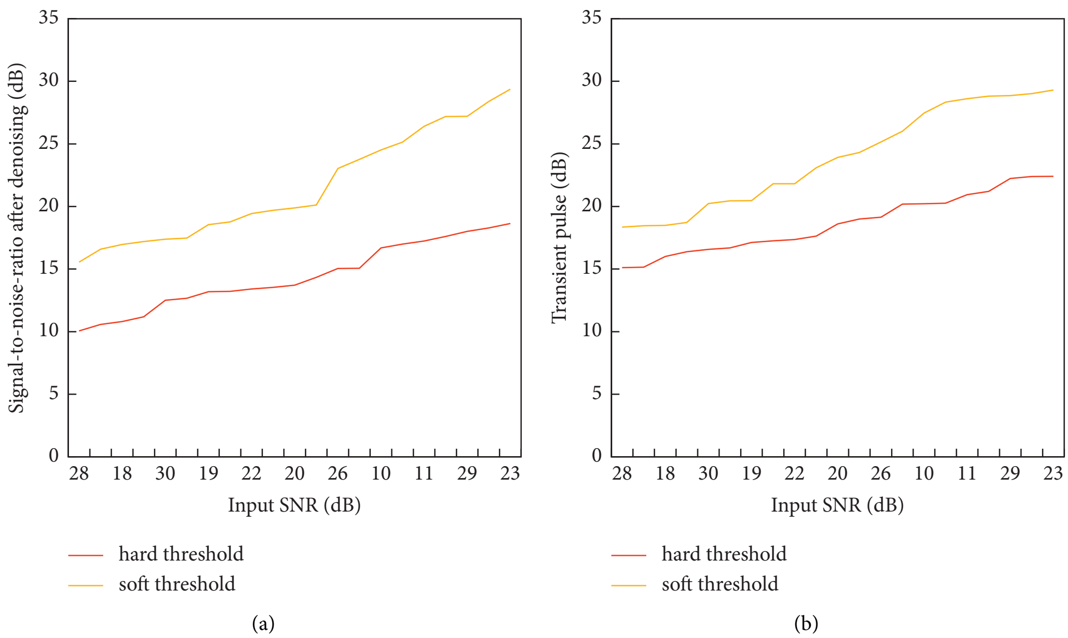


Figure 6: Comparison of signal-to-noise ratios after denoising of distribution network. (a) Voltage interruption test. (b) Transient pulse test.

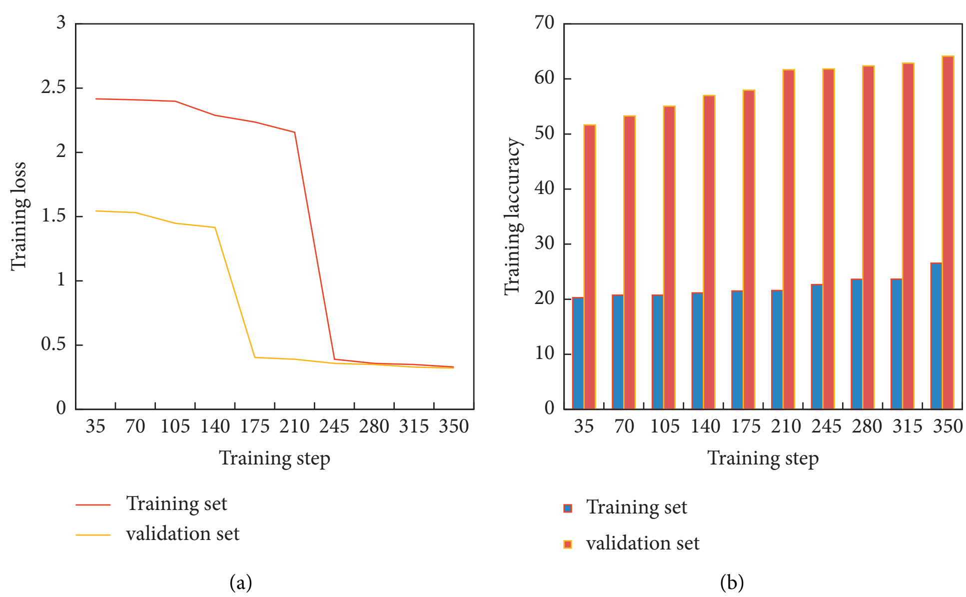


Figure 7: Training results. (a) Loss rate. (b) Accuracy.

The continuous improvement of the accuracy curve indicates that the classification effect of the model is getting better and better (the loss rate is shown in Figure 7(a)). The oscillation amplitude of the waveforms of the two curves is very small, the stability of the model continues to increase, and there is no over-fitting phenomenon (the accuracy rate is shown in Figure 7(b)).

The EMD decomposition analysis results of the distribution network voltage signal are shown in Figure 8. When the disturbance time is 0.06s–0.16s, the average value of the signal amplitude is 0.4005 V. The two positions with the largest frequency change are the start and end times of the disturbance, and the largest peaks at the disturbance time are the 614th point and the 1640th point, respectively; that is, the disturbance occurrence time is 0.0599 s–0.1602 s.

The signal is decomposed and reconstructed by two-dimensional wavelet thresholding deep neural network, and the decomposed signal is directly treated as the highest resolution signal. The wavelet at this time can be regarded as a pair of orthogonal complementary high- and low-pass filters. The detection results of the disturbance feature of this sag signal are shown in Table 2.

The basis function of wavelet is not unique, and all functions that satisfy the wavelet conditions can be used as

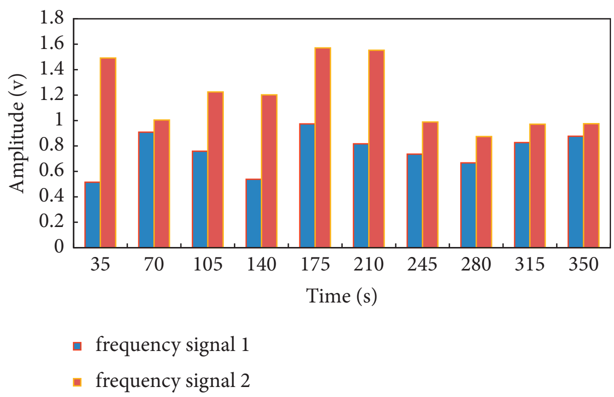


Figure 8: EMD decomposition analysis results of distribution network voltage signal.

Table 2: Detection results of disturbance features of sag signals.

Perturbation type	Perturbation feature	Theoretical value	Detection value
Voltage sag	Disturbance start (time/s)	0.0600	0.0599
	Disturbance termination (time/s)	0.1600	0.1602
	Voltage amplitude during (disturbance/V)	0.4000	0.4005

wavelet basis to analyze the signal. Therefore, when choosing a wavelet basis, it is necessary to consider its orthogonality, compactness, decay, symmetry, regularity, and vanishing moment. The detection results of the disturbance characteristic of the harmonic signal and the relative error with the theoretical value are shown in Table 3.

Assuming that a single-phase ground fault occurs in line 1, taking the fault point 3 km away from the busbar end as an example, the fault angle is 90°. In order to obtain as many data samples as possible, change the fault conditions as much as possible during simulation: 1) change the fault distance: the fault point starts from 1 km and increases by 100 m each time until 10 km; 2) change the grounding resistance: 10 g, 50 n, and 200 g; 3) change the failure angle: 30°, 45°, 60°, and 90°. The natural modal energy, active power, and fifth harmonic of each fault point are calculated, a total of 1200 sets of sample data are obtained, and these data are normalized. For comparison and verification, 900 groups are selected as the training samples of the fusion two-dimensional wavelet threshold deep neural network, and the remaining 300 groups are tested as the test samples. The test results of the fusion two-dimensional wavelet threshold deep neural network are shown in Table 4.

In reality, the electromagnetic environment of distribution lines is complex, and the traveling wave signal must be mixed with various noises when it propagates from the fault point to the measurement terminal. However, due to the complex and diverse noise components in reality, there is almost no external electromagnetic interference during simulation. Two noise signals with signal-to-noise ratios of 1 and 0.1 are artificially added in this section, and the abovementioned denoising methods and the wavelet variable threshold denoising proposed in this paper are used for different noises. The signal-to-noise ratio of the traveling wave signal is processed, and the denoising performance of these methods is compared. Since there is no electromagnetic interference generated by the outside world during the simulation, the noise in the fault traveling wave signal obtained by the simulation is not obvious. The sampling rate is 1 MHz, and the fault traveling wave signal is shown in Figure 9.

The signal-to-noise ratios of noisy signals I and II are 1 and 0.1, respectively. Noise-containing signals I and II are denoised by different denoising methods, respectively. The signal after denoising by this method is shown in Figure 10.

Mean square error and signal-to-noise ratio are usually used as evaluation indicators of denoising performance. The method in this paper is more ideal in terms of mean square

Table 3: Detection results of disturbance characteristics of harmonic signals and their relative errors with theoretical values.

Perturbation feature	Harmonic components	Theoretical value	Detection value
Frequency/Hz	Baseband	51	51.55
	3rd harmonic	151	158.12
	7th harmonic	353	352.15
Amplitude/V	Baseband	0.6	0.9842
	3rd harmonic	0.14	0.2902
	7th harmonic	0.12	0.1421

Table 4: Fusion 2D wavelet threshold deep neural network test results.

Fault distance (km)	Fault angle, transition power 10 Ω	Relative error (%)
1.2	1.2121	1.01
2.3	2.3113	0.37
3.0	2.9953	0.15
3.5	3.5336	0.99
3.0	3.0393	0.96
3.6	3.6163	0.36

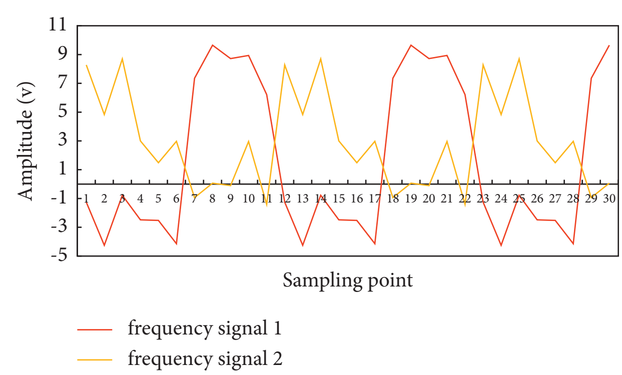


Figure 9: Fault traveling wave signal.

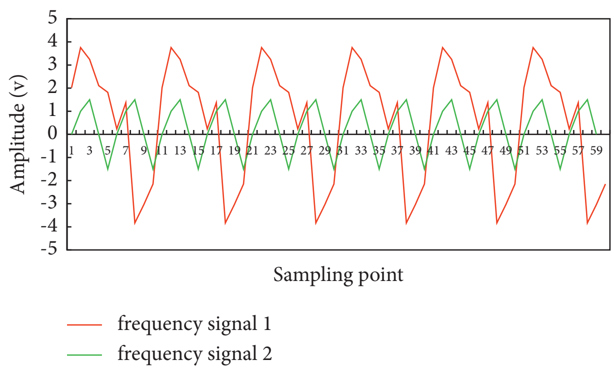


Figure 10: Signal after denoising by our method.

Table 5: Comparison of the method in this paper in terms of mean square error and signal-to-noise ratio.

Method	Mean squared error	Signal-to-noise ratio
Wavelet soft threshold	0.0106	10
Wavelet hard threshold	0.0104	12
2D wavelet thresholding	0.0102	14

error and signal-to-noise ratio. However, if the signal-to-noise ratio of the signal to be denoised changes greatly, the performance of each denoising method may also be different. Therefore, in the actual denoising process, the appropriate denoising method should be selected according to the specific situation of the noise. The comparison of the method in this paper in terms of mean square error and signal-to-noise ratio is shown in Table 5.

5. Conclusion

With the rapid development of electrical engineering distribution network, the number and total capacity of distribution transformers continue to increase, and the excitation inrush current of electrical engineering distribution network is becoming more and more serious, threatening the safe operation of the distribution network. Many new problems in the traditional electrical engineering distribution network prompt the fault location technology and device to adapt to the new situation and make corresponding changes. In order to effectively control and manage power quality problems, it is necessary to accurately classify power quality disturbance signals, and it is very important for disturbance classification to extract the feature quantities that can represent the key information of the signal from the denoised signal. This method can provide high-quality input data for load forecasting of electrical engineering distribution network and improve the accuracy of forecasting. According to the characteristics of the noise distribution after wavelet decomposition, the threshold value is improved, and the adjustable factor is introduced to make the constructed threshold value function have the advantages of traditional soft and hard threshold functions deal with. This paper conducts in-depth research on the practical problems faced by the identification and protection of electrical signal characteristics in distribution networks, which has important theoretical significance for improving the reliability of electrical engineering distribution networks, improving the efficiency of power troubleshooting, and promoting the rapid development of intelligent distribution networks. However, on the basis of soft and hard weighted threshold, this study explores the effect data of adaptive threshold wavelet processing. In future work, it can be considered that when formulating a feature extraction scheme, the selection of feature quantities is not the more the better, but the feature samples of the disturbance signal should contain the maximum disturbance information, and the features that can best reflect the disturbance difference should be selected.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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