

Article

A Hybrid Harmonic Detection Method Based on Wavelet Transform and Improved FFT Algorithm

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Abstract

In response to the current problems of asynchronous sampling, spectrum leakage, and the fence effect, this paper proposes a combination of FFT and wavelet transform to accurately analyze the steady-state and transient components in the signal, improving detection accuracy. Firstly, we use Newton interpolation to quasi-synchronize the original sampling sequence, achieving consistency between the sampling period and the actual period. Secondly, the modulus maximum method is used on the original signal to detect the presence of transient disturbances. The results indicate that quasi-synchronization can accurately correct the collected signals with high restoration and synchronization accuracy. The improved windowed interpolation FFT achieves a detection accuracy of 0.3% for steady-state harmonics. The wavelet divides the frequency band and uses modulus maxima to detect signal singularity, accurately extracting transient disturbance signals with an accuracy of up to 5%. Similarly, for complex power signals, the analysis of hybrid algorithms also meets practical engineering needs.

Keywords: harmonic signal; improved FFT; wavelet transform; modulus maximum method

1. Introduction

As the pillar energy of today's social development, electricity plays a crucial role in promoting the progress of social technology, continuously improving people's production and living standards, and maintaining the safe, stable, and healthy development of human society. With the introduction of the global energy internet, mankind aims to realize the replacement of fossil energy with clean energy and the replacement of other energy consumption with electric energy consumption, which has given the strategic significance of the era to electric energy. To ensure the stable operation of the power system, accurate analysis of grid signals has become the primary task in improving power quality [1].

With the continuous improvement of the intelligence level of large-scale industrial production, electrical equipment in the power grid is complex and diverse, the harmonics in the power network exhibit characteristics such as nonlinearity, fluctuation, and randomness [2–6], and the influencing factors are complex and intricate. The power system is composed of bidirectional symmetrical components, which generate voltage and current with half-wave symmetry characteristics. Due to the half-wave symmetry characteristics, harmonics are cancelled out, so even harmonics can be ignored in most power systems. Harmonics in the power grid are divided into even harmonics and odd harmonics. Generally, the harm of odd harmonics is greater than that of even harmonics, especially when



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a large number of 166 3rd harmonics affect the signal. In order to accurately measure the key parameters of harmonic signals in the power grid, extensive research has been conducted in the field of detection technology. With the continuous deepening of research on harmonic detection technology, there are mainly two types of harmonic detection methods based on time-domain analysis and frequency-domain analysis [7]. The representative time-domain analysis method is the harmonic detection algorithm based on instantaneous reactive power theory, which is mainly applied in the design of active filters. The frequency domain analysis method is currently the most widely used detection method, with typical applications including Fourier transform, wavelet transform, modern spectral estimation, neural networks, etc. [8,9].

The discrete Fourier transform (DFT) has been well studied to deal with the spectral leakage and picket fence effects in frequency estimation [10–12]. The DFT method has good real-time performance and greater flexibility in selecting the number of points or sampling rate. However, DFT requires a large amount of computation. The harmonic detection algorithm based on Fast Fourier Transform (FFT) is currently the most widely used in the field of harmonic detection [13]. FFT is developed on the basis of DFT, which converts electrical signals from the time domain to the frequency domain through Fourier transform [14]. By using frequency domain information, the amplitude, frequency, and phase of harmonic components can be easily solved. This method has a simple principle, a fast calculation speed, and is easy to implement in engineering. However, FFT requires sampling the signal with integer multiples of the sampling period, resulting in weak real-time and tracking capabilities of the algorithm [15–17]. During application, issues such as spectrum leakage and the fence effect can affect detection performance, thereby limiting the application of this method. At present, there are three main methods to suppress spectrum leakage. The first is to add a window function for truncation preprocessing and then correct the detection results through an interpolation algorithm. Window truncation can effectively reduce spectrum leakage, and interpolation algorithms can suppress the fence effect, thereby accurately measuring the amplitude, frequency, and phase parameters of each harmonic. In reference [18], a power harmonic detection algorithm with four minimum sidelobe window double spectral line interpolation corrections was proposed, and the relative error of the amplitude detection results reached the order of 10–4%. Based on the three spectral line interpolation algorithm, reference [19] proposed the Galef Vincent window three spectral line interpolation correction algorithm. The relative error of the amplitude detection result reached the order of 10–6%, which is two orders of magnitude higher than the detection accuracy in reference [20]. The second is to adjust the ideal sampling frequency [21]. This method improves the detection accuracy of the algorithm by modifying the actual sampling sequence to become an ideal sampling sequence synchronized with the sampling signal. This method has low computational complexity and a good dynamic response and is suitable for real-time harmonic measurement [22]. The third is to use a digital phase-locked loop (DPLL) to achieve synchronous sampling [23]. A DPLL can lock the frequency of the test signal, keeping the two synchronized, and use the synchronization signal to control the sampling process. Reference [24] was based on quasi-synchronous DFT harmonic analysis and used the least squares method to reduce frequency offset, improving the detection accuracy of the algorithm. However, the operation process requires a second iteration, resulting in poor real-time performance. Reference [25] established a linear correction model for quasi-synchronous DFT harmonic phase angle and sampling signal frequency offset, iteration number, and harmonic number. By measuring the frequency offset of the signal, the harmonic detection results were corrected, effectively suppressing spectral leakage in a short range. The harmonic detection algorithm based on Fourier transform has matured, and existing harmonic detection devices are designed based on this principle.

The harmonic measurement method based on wavelet transform overcomes the global problem of Fourier transform in both time and frequency domains and utilizes its excellent localization analysis ability to achieve accurate measurement of non-stationary harmonic signals [26]. The key to wavelet transform lies in the selection of wavelet bases, but there is currently a lack of systematic regulations for the selection of wavelet bases, which can only rely on experience and increase the uncertainty of the algorithm. Moreover, as the decomposition level is refined, the computational complexity rapidly increases, resulting in poor real-time performance. The harmonic detection algorithm based on wavelet transform suffers from spectral aliasing, which affects the accuracy of the detection results [24]. Reference [25] proposed a harmonic detection algorithm that combines windowed interpolation FFT and wavelet packet transform. Through windowed FFT, spectrum leakage and the fence effect are reduced. At the same time, wavelet packet transform was used to divide frequency bands, and only the required frequency bands were decomposed and reconstructed, reducing the computational complexity of the algorithm and improving the real-time detection performance. In order to solve the above technical problems, the technical solution adopted in this paper by the present invention is to use wavelet transform to analyze the separation of high-frequency and low-frequency information in the signal and reconstruct the steady-state and transient signals. The position of each mutation point in the signal is detected by the modulus maximum, and high-frequency mutation information is extracted. By using windowed interpolation and Hanning window truncation for low-frequency steady-state components, discrete signals are obtained. FFT is used to perform fast Fourier transform on the discrete signals, and the obtained spectral information is corrected for errors caused by spectral leakage and the fence effect using the double line spectral interpolation method in windowed interpolation. The amplitude and phase information of harmonics are accurately extracted, and the amplitude and frequency information of the fundamental wave and each harmonic are finally obtained. The method proposed in this paper provides an effective and feasible approach for harmonic detection. Quickly identifying, accurately analyzing, and classifying waveform changes in the power grid is of great practical significance and economic value for improving the stable operation of the power supply system and promoting socio-economic development.

2. Theoretical Analysis of the Harmonic Detection Method Based on Fourier Transform

2.1. Continuous Fourier and Discrete Fourier

Periodic voltage and current signals can be represented by a periodic function with a basic period of T :

$$f(t) = f(t + kT) \quad (k = 0, 1, 2, \dots) \quad (1)$$

The Fourier series representation of non-sinusoidal periodic functions is:

$$f(t) = a_0 + \sum_{n=1}^{\infty} (a_n \cos n\omega_0 t + b_n \sin n\omega_0 t) \quad (2)$$

Among them, a_0 is the DC component, a_n is the cosine coefficient of the n -th harmonic, and b_n is the sine coefficient of the n -th harmonic.

According to Euler's formula:

$$\begin{aligned} e^{j\omega t} &= \cos \omega t + j \sin \omega t \\ e^{-j\omega t} &= \cos \omega t - j \sin \omega t \end{aligned}$$

$$\begin{aligned}
 f(t) &= a_0 + \sum_{n=1}^{\infty} \left[\frac{1}{2} a_n (e^{j\omega t} + e^{-j\omega t}) - \frac{1}{2} j b_n (e^{j\omega t} - e^{-j\omega t}) \right] \\
 &= a_0 + \sum_{n=1}^{\infty} \left[\frac{a_n - j b_n}{2} (e^{jn\omega t} + e^{-jn\omega t}) + \frac{a_n + j b_n}{2} e^{-jn\omega t} \right] = \sum_{n=-\infty}^{+\infty} F_n e^{jn\omega t} \\
 F_n &= \frac{1}{2} (a_n - j b_n) = \frac{1}{2} \sqrt{a_n^2 + b_n^2} e^{j\theta_n} = \frac{1}{2} A_n e^{j(\theta_n - \pi/2)}
 \end{aligned} \tag{3}$$

The continuous function $f(t)$ in the time domain satisfies the Dirichlet condition and is absolutely integrable. Its Fourier transform and its inverse Fourier transform are:

$$\begin{aligned}
 F_n(\omega) &= \int_{-\infty}^{+\infty} f(t) e^{-j\omega t} dt \\
 f(t) &= \frac{1}{2\pi} \int_{-\infty}^{+\infty} F(\omega) e^{j\omega t} d\omega
 \end{aligned} \tag{4}$$

2.2. Interpolation Spectral Analysis of Window Functions

Take a test signal with a frequency of f_0 and a sampling frequency of f_s : $x(n) = A \cdot \sin(2\pi \frac{f_0}{f_s} n)$, the truncated continuous Fourier transform representation with window function $w(n)$ is:

$$x(f) = \sum_{n=0}^{\infty} x(n) \cdot w(n) \cdot e^{-2\pi f n} = \frac{A}{2j} e^{j\theta} W\left(\frac{2\pi(f - f_0)}{f_s}\right) \tag{5}$$

Discretize the above equation, $f = k \cdot \Delta f$, frequency resolution $\Delta f = f_s / N$:

$$X(k \cdot \Delta f) = \frac{A}{2j} e^{j\theta} W\left(\frac{2\pi(k \cdot \Delta f - f_0)}{f_s}\right) \tag{6}$$

Due to the difficulty of spectral lines falling exactly on the peak point during signal sampling, the two adjacent maximum and second-largest spectral lines k_1 and k_2 closest to the peak point can be used to obtain the peak point frequency $k_1 \leq k \leq k_1 + 1$. Amplitude $y_1 = |X(k_1 \cdot \Delta f)|$ and $y_2 = |X(k_2 \cdot \Delta f)|$, $\alpha = k - k_1 - 0.5$. The range of values for α is $[-0.5, 0.5]$.

From two actual spectral lines, it can be inferred that:

$$\beta = \frac{y_2 - y_1}{y_2 + y_1} = \frac{|W[2\pi \cdot (-\alpha + 0.5/N)]| - |W[2\pi \cdot (-\alpha - 0.5/N)]|}{|W[2\pi \cdot (-\alpha + 0.5/N)]| + |W[2\pi \cdot (-\alpha - 0.5/N)]|} \tag{7}$$

The expression after polynomial approximation is

$$\alpha = F^{-1}(\beta) = \alpha_1 \beta + \alpha_3 \beta^3 + \dots + \alpha_{2n+1} \beta^{2n+1} \tag{8}$$

The harmonic signal frequency correction value can be obtained:

$$f = k \Delta f = (k_1 + \alpha) f_s / N \tag{9}$$

Harmonic signal phase correction value:

$$\phi = \arg[X(k_1 \Delta f)] - \pi(\alpha + 0.5) \tag{10}$$

Weighted average of two spectral lines y_1 and y_2 to obtain the amplitude:

$$A = \frac{(y_1 + y_2) \cdot (b_0 + b_2 \alpha^2 + \dots + b_{2l} \alpha^{2l})}{N} \tag{11}$$

By using data fitting methods, different window functions are corrected in frequency, phase, and amplitude. The correction formula is as follows:

Hanning window function:

$$\begin{aligned}\alpha &= 1.5\beta \\ \theta &= \arg[X(k_i\Delta f)] + \frac{\pi}{2} - \pi(\alpha - 0.5(-1)^i) \quad i = 1, 2 \\ A_m &= \frac{(Y_1 + Y_2) \cdot (2.35619403 + 1.15543682\alpha^2 + 0.32607873\alpha^4 + 0.07891461\alpha^6)}{N}\end{aligned}\quad (12)$$

2.3. Establishment of Signal Model for Power System

The power signals in the power grid are complex, including harmonic distortion and external disturbances, which can cause frequency and waveform instability and affect the quality of electricity consumption. In the process of detecting and analyzing power signals, the components, amplitudes, and generation times of the signals are recorded in order to take measures to reduce their harm to the power environment. Harmonics in the power grid are divided into even harmonics and odd harmonics. Generally, the harm of odd harmonics is greater than that of even harmonics, especially when a large number of 3rd harmonics affect the signal. In addition to harmonics, it also includes sudden and nonlinear interference signals. So, in the model, representative signal components are selected based on the actual signals and analysis requirements for establishment. The ideal power signal is:

$$x = 6 * \sin(2 * \pi * 5 * t) + 3 * \sin(2 * \pi * 15 * t) \quad (13)$$

3. Theoretical Analysis of the Disturbance Detection Method Based on Wavelet Transform

Short time Fourier transform can obtain the time-frequency characteristics of a signal, which are obtained by translating the window function. Once the window size is fixed, the frequency resolution is also determined. Wavelet analysis decomposes a signal into a series of functions obtained by stretching and translating the mother wavelet, which not only yields the frequency components but also the time position of the frequency in the time domain.

3.1. Continuous Wavelet and Discrete Wavelet

Adding a limit condition to a square integrable function $\varphi(t)$ gives the permissibility condition:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty \quad (14)$$

$\varphi(t)$ is called the mother wavelet function, which is a rapidly oscillating decay function with a mean of zero. The Fourier transform expression is $\hat{\psi}(\omega) = \int_{-\infty}^{+\infty} \psi(t)e^{-j\omega t} dt < \infty$. After stretching and translating the mother wavelet $\varphi(t)$, it is obtained:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad a, b \in \mathbb{R}; a \neq 0 \quad (15)$$

a is the wavelet basis function; where a is the scaling factor, b is the translation factor, and the scale a controls the scaling of the wavelet function. The larger a is, the wider the wavelet function is, and the smaller the value. The translation amount b controls the translation of the wavelet function, and the translation amount corresponds to time.

For any finite signal $f(t) \in L^2(\mathbb{R})$, its continuous wavelet:

$$WT(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt = \langle f(t), \psi_{a,b}(t) \rangle \quad (16)$$

In continuous wavelet transform, a and b are continuously changing, and the time-frequency window also moves continuously on the time-frequency plane, so there is infor-

mation redundancy in continuous wavelet transform. Moreover, in practical applications, especially in computer information processing, continuous wavelets must be discretized. It is worth noting that although wavelet discretization analyzes continuous time signals, it does not discretize the time t , but rather the scale parameter a and translation parameter b .

The discrete formulas for the scale parameter a and translation parameter b are usually taken as $a = a_0^j$, $b = ka_0^j b_0$, corresponding to the discrete wavelet function:

$$\psi_{j,k}(t) = a_0^{-j/2} \psi\left(\frac{t - ka_0^j b_0}{a_0^j}\right) = a_0^{-j/2} \psi(a_0^{-j} t - kb_0) \quad (17)$$

And discretized wavelet transform coefficients:

$$C_{j,k} = \int_{-\infty}^{+\infty} f(t) \psi_{j,k}^*(t) dt = \langle f, \psi_{j,k} \rangle \quad (18)$$

Its reconstruction formula:

$$f(t) = C \sum_{-\infty}^{+\infty} \sum_{-\infty}^{+\infty} C_{j,k} \psi_{j,k}(t) \quad (19)$$

3.2. Signal Detection Based on Wavelet Transform

The start and end times of sudden changes in voltage, such as temporary rises and falls, often correspond to singular points in the voltage signal. Due to the fast decay of wavelet functions, they have strong adaptability and can adjust the time and frequency window widths. They have outstanding advantages in reflecting the local characteristics of the signal in the time-frequency domain and can detect sudden signals, achieving accurate determination of the time when signal disturbances occur.

If $\varphi(t)$ is the first derivative of a low-pass smoothing function $\theta(t)$. $\varphi(t)$ satisfies the wavelet function tolerance condition; take the scale factor a as the scaling factor of $\theta(t)$, $\theta_a(t) = \frac{1}{a} \theta(\frac{t}{a})$. Perform wavelet transform on scale factor a :

$$\psi_a(t) = \frac{1}{a} \psi\left(\frac{t}{a}\right) = \frac{d\theta(\frac{t}{a})}{dt} = a \frac{d\theta_a(t)}{dt} \quad (20)$$

Using the wavelet basis function $\varphi(t)$ to perform wavelet transform on signal $f(t)$ at scale a :

$$WT_f(a, t) = f(t) * \psi_a(t) = f(t) * \left[a \frac{d\theta_a(t)}{dt} \right] = a \frac{d}{dt} [f(t) * \theta_a(t)] \quad (21)$$

4. Combining the Wavelet Transform and Improved FFT Algorithm

4.1. Principle of the Joint Algorithm

Based on the analysis and discussion of complex and variable power grid signals with different components, this paper combines improved Fourier transform and wavelet modulus maximum detection to detect and analyze steady-state harmonics and transient interference signals of power quality. Specifically, using software algorithms to correct signal data, achieving a quasi-synchronous sequence with a sampling frequency consistent with the actual frequency, reducing sampling deviation, and solving the problem of asynchronous sampling. For the spectrum analysis of the harmonic steady state, the FFT method with a Hanning window and double spectral line interpolation is adopted to reduce the errors caused by spectrum leakage and the fence effect and accurately extract harmonic amplitude, phase, and other information. For some transient disturbances, the wavelet Mallat method is used to decompose the signal, detect signal singularity using modulus maxima, extract high-frequency mutation information, and clearly display the occurrence

time and degree of disturbance. Figure 1 shows the schematic diagram of the transient and steady-state analysis of power quality.

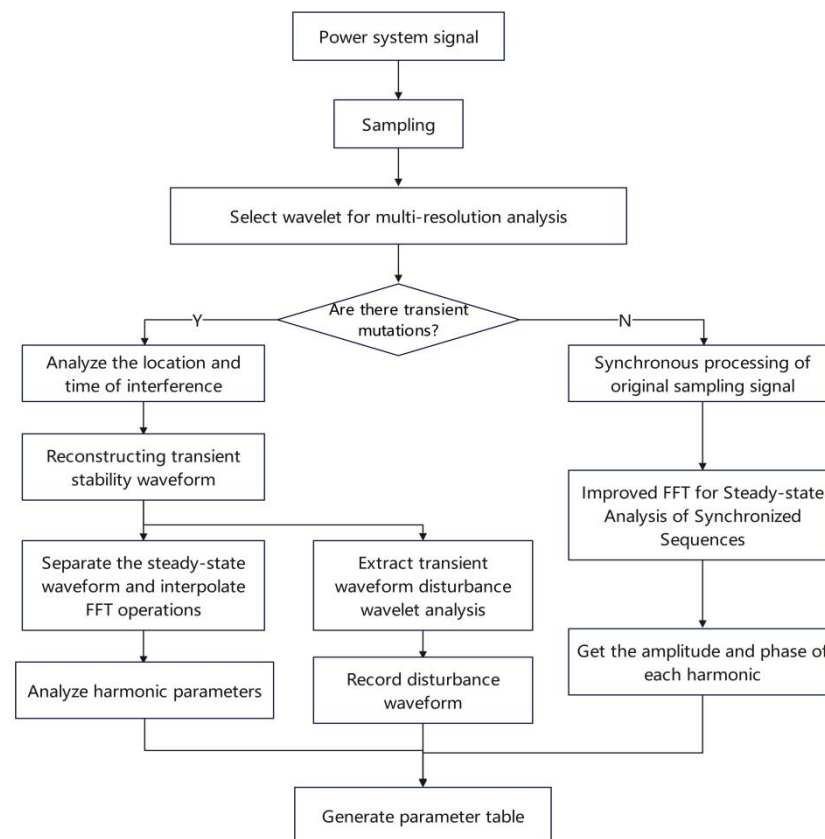


Figure 1. Signal processing diagram of harmonic detection method.

4.2. Quasi-Synchronous Detection Analysis of Newton Interpolation

Newton interpolation is the process of extracting the entire period of a sampling sequence through forward Newton interpolation and then synchronizing and adjusting the sampling sequence through reverse Newton interpolation. Sample the power grid signal at a certain sampling frequency, and calculate the fundamental period of the power grid by finding waveform feature points; that is, the sequence length corresponding to the signal within the period. The characteristic points of a frequency generally include peaks, valleys, and zeros. However, due to sampling errors, the peaks and valleys are not accurate. Therefore, this paper selects the zero point with the highest waveform slope to improve accuracy and collects the length of the ten-frequency sequence for calculation. The key to synchronous interpolation lies in determining the relative position between the interpolation point and the original sampling sequence point, using the calculated quasi-fundamental period as the interpolation interval, and performing equidistant interpolation on the sampled signal to obtain a quasi-synchronous sequence.

The specific calculation steps are: taking the full cycle signal of the actual power grid signal and searching for the zero crossing points at both ends. Perform Newton interpolation on the four surrounding data points to find the accurate zero crossing moments, denoted as t_{start} and t_{end} , and calculate the time-domain length of the ten cycle signals in the sampling sequence. Due to the constant number of points calculated each time, it can be known that at a frequency of 50 Hz in the power grid, the sampling length of ten cycles is $n_0 = f_s/50 \times 10$. The time-domain length of the forward interpolated signal is synchronized into a sequence of length n_0 , with interpolation positions at n equal points of $t_{\text{end}} - t_{\text{start}}$. The amplitude of the original sampled signal at each equal point is obtained by

reverse Newton interpolation using the data near each equal point, and the length of the synchronized sequence obtained is still n_0 .

4.3. Experimental Results

To verify the accuracy of the proposed method in this paper, the simulation and experiment were carried out using Matlab/Simulation. Firstly, the waveform of the constructed power signal is shown in Figure 2, including the ideal signal, noise signal, and mixed signal. Secondly, the amplitude frequency diagram of the power signal was obtained with the FFT. The signal amplitude frequency phase frequency information could be accurately obtained, which is shown in Figure 3. The new power signal was obtained by using wavelet analysis for denoising, as shown in Figure 4. Meanwhile, it performed five-layer wavelet decomposition on the newly obtained signal, as shown in Figure 5. Finally, the signal was reconstructed using wavelet transform. For the reconstructed steady-state waveform of the decomposed low-frequency signal shown in Figure 6, the separated signal was subjected to the windowed interpolation FFT algorithm for harmonic spectrum analysis. The results show that wavelet transform can accurately separate high-frequency and low-frequency information in signals and reconstruct steady-state and transient signals. The reconstructed waveform information is relatively accurate. However, in terms of steady-state harmonic detection, especially between harmonics and interharmonics with similar frequencies, wavelet transform is not as intuitive as Fourier calculation and increases algorithm complexity, which affects the calculation results. For non-stationary signals with abrupt interference, wavelet transform, due to its time-frequency characteristics, can accurately locate the disturbance location and determine the disturbance type with high accuracy, solving the problem of Fourier in this regard. Each harmonic voltage is set to 0.5% and 1% of the fundamental wave. By synchronously collecting the power grid signal, the measurement frequency accuracy error is less than 0.01 Hz. The accuracy results of each detected harmonic voltage are shown in Table 1. There is a slight deviation between the amplitude theory and the measured value, but within the allowable error range of 0.3%. The amplitude accuracy of various transient types, as shown in Table 2, has also reached 5%. We found that the method proposed in this paper is accurate and reliable, as shown in Table 3.

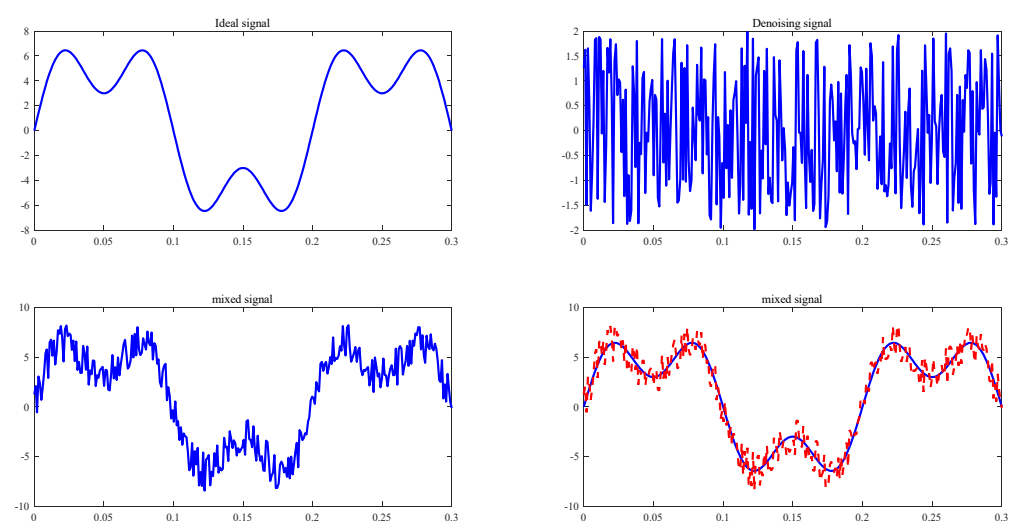


Figure 2. Ideal signal, noise signal, and mixed signal.

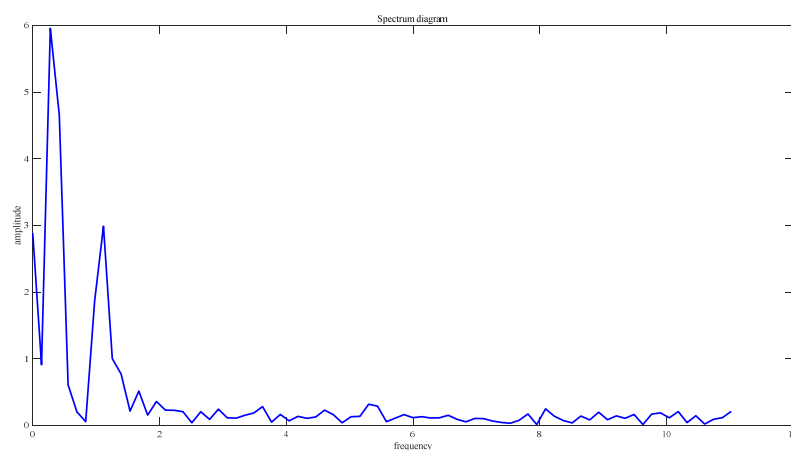


Figure 3. FFT processing amplitude frequency diagram of power signal.

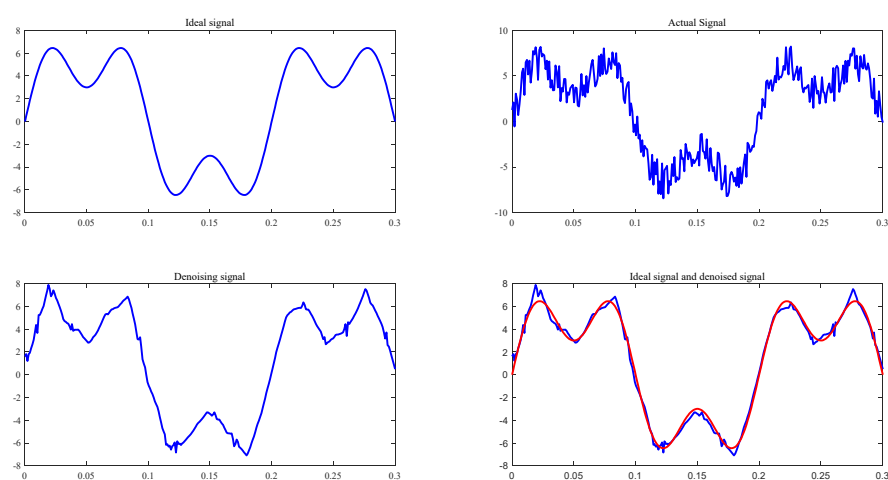


Figure 4. Ideal signal, actual signal, and denoising signal.

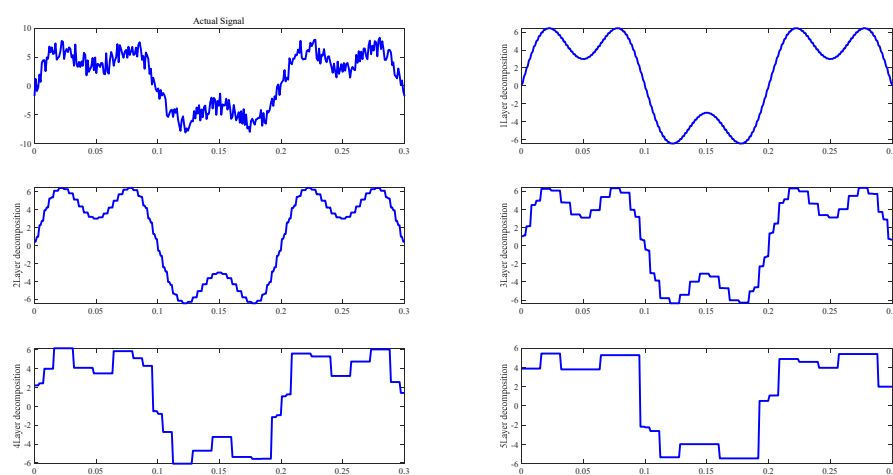


Figure 5. Power signal decomposition.

Table 1. Harmonic analysis accuracy test.

Harmonic Frequency	0.5%	Error	1%	Error
3	0.503%	0.003%	1.23%	0.23%
5	0.507	0.007%	1.08%	0.08%
7	0.518	0.018%	1.19%	0.19%

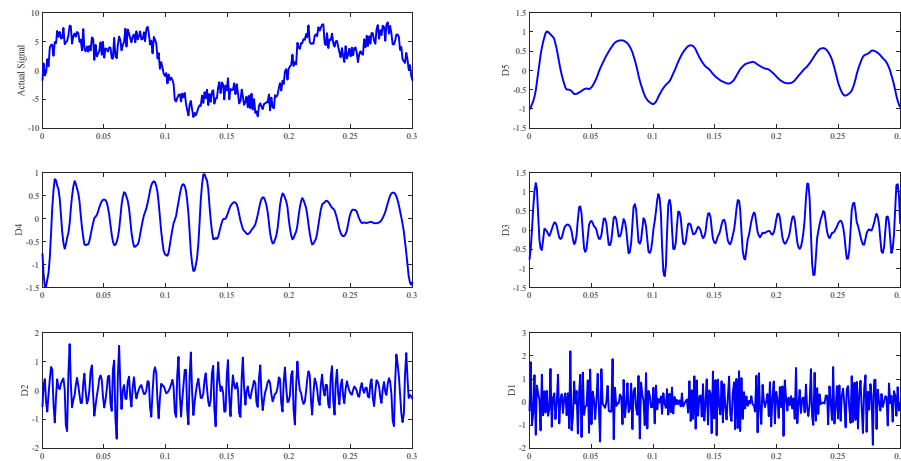


Figure 6. Reconstructed waveform diagram of power signal.

Table 2. Transient characteristic accuracy test.

Harmonic Frequency	True Value (V)	Measurement Value (V)	Error
Temporary increase	2	2.038	0.19%
Temporary decrease	4	3.986	0.35%

Table 3. Comparison of error in the paper and Refs. [7,23,27].

Method	Harmonic Error	Transient Error	Phase Error	Relative Error
Reference [7]	2.09%	—	3.65%	9.03%
Reference [23]	2.1%	14.7%	2.25%	4.32%
Reference [27]	0.47%	4.7%	1.53%	2.06%
This paper	Within 0.3%	Within 5%	0.95%	1.12%

5. Conclusions

This paper uses Mallat and modulus maximum detection algorithms based on fast Fourier transform and wavelet transform to detect and analyze steady-state and non-stationary components in power system signals. By correcting the original sampling data to achieve quasi-synchronous sampling, the analysis method combining Fourier transform and wavelet transform is improved. The accuracy of the algorithm is demonstrated through MATLAB platform model simulation and experiments, improving detection accuracy and reducing the harm caused by power grid pollution from the source analysis. The main work summary is as follows:

- (1) Analyze the current detection methods for power quality, with voltage signal detection as the main focus, and construct a power signal model. By using the Hanning window function and its interpolation-corrected FFT algorithm to achieve spectrum analysis of steady-state harmonics in signals and completing algorithm simulation, it is verified that it reduces errors caused by spectrum leakage and the fence effect in steady-state signal frequency domain analysis. Based on the actual situation of power signal analysis, select appropriate wavelets and use modulus maximum points to detect signal singularity. Construct a signal model and complete an algorithm simulation to verify the accuracy of the wavelet transform in extracting and identifying transient interference in time-domain analysis.
- (2) In response to the drawbacks that arise during the actual detection process, a comprehensive detection scheme is validated by combining the advantages of windowed

interpolation FFT harmonic analysis and wavelet detection algorithms. For asynchronous sampling, the Newton interpolation algorithm is used to synchronize and correct the original sampling sequence. Perform steady-state and transient identification on signal decomposition, and process and analyze different decomposed signals separately. Based on the complex signals present in the power grid, a mathematical model was constructed to verify the reliability and accuracy of the algorithm. The accuracy of harmonic analysis can reach 0.3%, and the accuracy of transient feature recognition can reach 5%.

- (3) A hybrid harmonic detection method based on wavelet transform an improved FFT algorithm is proposed in this paper. This method has good accuracy and reliability. However, it should be noted that this work does not take into account actual complex working conditions. Therefore, it is necessary for future research to implement an optimal method in complex environments.

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