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# Review of Feature Extraction Methods for Power Equipment Monitoring Data

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**Abstract:**The breadth and depth of on-line monitoring of power transmission and transformation equipment have been greatly enhanced in the smart grid environment. Time sequence waveform signals are important basis for condition assessment and fault diagnosis of power transmission and transformation equipment, because they occupy a large amount of monitoring data. However, it is difficult to use directly the time sequence waveform signals as machine learning algorithm inputs because of their high dimensionality and large volume. So, feature mining in time sequence waveform signals is the basis and key for subsequent pattern recognition and fault diagnosis. In this paper, the feature extraction is deeply studied for time sequence waveform signal of power equipment monitoring combining with the frequency spectrum analysis and nonlinear dynamics analysis.It intends to provide a reference for further research.

**Keywords:**condition monitoring data; feature extraction; spectrum analysis; nonlinear dynamics analysis

## 1. Introduction

The power system has been developing towards large capacity, ultra-high voltage and cross-regional direction, when the national smart grid construction is fully implemented. It puts forward higher requirements for automated safe and stable operation of power transmission and transformation equipment. At the same time, it is imperative to carry out more extensive and in-depth online monitoring of the power equipment which can help to obtain precise status data, so as to realize accurate evaluation of the operation status and find its internal inherent defects and local hidden dangers caused by long-term operation as soon as possible. It can enhance the stability and security of the system. Among the monitoring data of many power equipment in power network, the time series waveform signal data which has a larger proportion is an important basis for evaluating the status and fault diagnosis of power transmission and transformation equipment. Due to the high dimension and large volume of time series waveform signal, it is not easy to be directly used as machine learning algorithm input. Therefore, feature mining from time-series waveform signals is the foundation and key of subsequent pattern recognition and fault diagnosis.

In the power system, strong magnetic fields, strong electric fields, frequently changing modes of operation and change of operating environment often affect the collection of on-line monitoring signals. The feature extraction of signals has the characteristics of multidisciplinary cross fusion. We can excavate rich spectrum characteristics and nonlinear dynamic index characteristics from the time series waveform signals monitored by power equipment.

In this paper, the timing waveform signal in power equipment monitoring is taken as the research object. Based on the comprehensive review of the previous research results, this paper summarizes the research challenges, progress, application fields and development trends of relevant issues. It intends to provide a reference for further research.

## 2. Feature Extraction Method of Power Equipment Monitoring Waveform Signal

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### *2.1 Feature Extraction Method Based on Spectrum Analysis*

Common power equipment monitoring time series waveform signals include partial discharge signal, vibration signal, ultrasonic signal, UHF signal and leakage current signal, etc. Time-series waveform signals are recorded with time as references. It means that it is difficult to get the basic properties of the data from a direct view. In other words, simple and intuitive time domain analysis can only represent the change of signal amplitude with time, and it is difficult to clearly indicate the information such as the frequency composition, the size of each frequency component and the change of frequency with time, except the simple harmonic of single frequency component.

Therefore, the timing waveform signal is hard to directly use in the status diagnosis of equipment. Spectral analysis is usually used to convert the data from the time domain to the frequency domain. Then, the characteristic quantity of the data is obtained by analyzing the characteristics of the frequency domain, so as to attain the purpose of analyzing the data. Frequency domain analysis is one of the most widely used signal processing methods in equipment fault diagnosis. Spectral analysis methods that have been applied to power network analysis include Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT) [1, 2], Gabor [3] Transform and wavelet Transform [4, 5], etc.

FFT can decompose the signal as a whole into different frequency components. However, it lacks local information, that is, it cannot get the information of when a certain frequency component occurs, which is very important for non-stationary and nonlinear signals, while many online monitoring signals of electrical equipment (such as insulation discharge current or UHF signals) belong to non-stationary signals.

From the perspective of method, STFT uses a central symmetric sliding window function to intercept the observed signals, and performs Fourier transform on the short-time signals at different moments, and finally obtains the time spectrum composed by the signals of each frequency band. Therefore, the analysis effect of STFT on signals depends on the selected window function. In addition, since the size and shape of STFT window cannot change with the frequency of signals, that is, the fixed window function also makes it impossible for STFT to obtain good resolution in both time domain and frequency domain of broadband signals.

Gabor transform is the optimal SHORT-time Fourier transform under Heisenberg uncertainty criterion. It's the STFT with the Gaussian window function. It establishes the joint time-frequency function of non-stationary signal by means of signal time-shift and frequency modulation. Compared with STFT, Gabor transform has better time-frequency aggregation [3] and has the function of window translation. However, this method still adopts fixed window function, which cannot achieve good resolution in both time domain and frequency domain.

Wavelet transform uses multi-resolution techniques. It enables a scale-variable time-frequency window with good time-frequency localization characteristics suitable for non-stationary signal analysis. However, it is challenging to determine the wavelet base and the number of decomposition layers. It cannot accomplish the adaptive decomposition of signals. Once the wavelet base is selected, it cannot be altered during the whole signal analysis process. The global optimal wavelet basis may not obtain good effect locally and may even have the worst effect. Different wavelet basis analysis of the same signal is also very different, which is a very important reason to influence the application of wavelet transform engineering. In addition, wavelet transform decomposed one-dimensional signal into time-scale domain, not the time-frequency domain in the strict sense and could not provide an intuitive time-frequency representation method.

*2.2 Feature Extraction Method Based on Nonlinear Dynamic Index*

At present, spectral analysis and nonlinear analysis are typically used in signal analysis. Spectral analysis is to transform the signal from time domain to frequency domain information with less data and more obvious features. It can evaluate the state of equipment by observing the amplitude, energy and power of the signal in the frequency domain. It has been widely used in power monitoring signal analysis. But it has a great limitation if only using frequency-domain features to distinguish fault types. Because some or even most of the spectrum of different types of fault signals overlap, it is difficult to distinguish them in the frequency domain [6].

Chaos, bifurcation and fractal theory are three important branches of nonlinear science. Nonlinear analysis treats the object of study as a dynamic system. It uses some nonlinear dynamics indicators to study the nonlinear dynamics law contained in the time series signals. This method has attracted the attention of many disciplines in recent years, and its application in materials, electronics, physics, life science and other fields shows more and more advantages of its distinctive analysis method. At present, the popularly used nonlinear dynamic indexes include fractal dimension, Lyapunov index, entropy and complexity, etc.

The research object of fractal theory is the non-smooth and non-differentiable geometric form produced by nonlinear systems. The obvious characteristic of fractal structure is the similarity between local and global morphology, and the corresponding characteristic index parameter is the fractal dimension. The common fractal dimensions are box dimension, information dimension, correlation dimension and generalized dimension. Fractal dimension is not only used to quantify the self-similar properties of fractal structures, but also the size of fractal dimension can be used as a characteristic index of whether chaotic motion occurs in the dynamic system [9]. Literature [10] designed five discharge models focusing on the internal partial discharge and external discharge interference of high-voltage equipment. It extracts the fractal dimension of the partial discharge gray image, the second order generalized fractal dimension and the fractal dimension of the partial discharge high value gray image, which together constitute the partial discharge pattern recognition features which has a good recognition effect.

The basic characteristic of chaotic motion is that motion is very sensitive to initial conditions. An orbital produced by two very close initial values, separated exponentially over time. The Lyapunov index is the quantity that describes this phenomenon. In 1983, G. Rebogi demonstrated that the existence of chaos could be confirmed as long as the maximum Lyapunov index was greater than zero. Chaos can be determined by calculating the maximum Lyapunov exponent of the sequence in practical application. Reference [13] measured the IEC(B) electrode discharge pulse current signal of 150 m thick polyester film. Then, the maximum Lyapunov index of the discharge time series is positive and the correlation dimension is non-integral value, which proves that the partial discharge phenomenon generated by IEC(B) electrode system has chaotic characteristics. Literature [14] used chaotic characteristic quantities such as maximum Lyapunov index, correlation and Kolmogorov entropy, which were used to detect partial discharge. It achieved good results. Literature [15] reconstructed the phase space of each phase sequence in the three-dimensional spectrogram of GIS PD. The maximal Lyapunov exponent features under different phase sequences were extracted to construct the feature set. It is verified that this method has strong recognition ability especially for air gap defects. Literature [16] analyzed the phase diagram and the maximum Lyapunov index after the phase space reconstruction of the vibration signals on the surface of the transformer oil tank, which proved that the time series of the transformer vibration signals had chaotic characteristics.

The entropy and complexity of a system imply the motion law of the whole system, and their physical meaning is directly related to the property of a single variable of the system. In 1854, Clausius first introduced the state function entropy S in the study of thermodynamic process, which can be used to determine the direction and limit of the process occurring in adiabatic process and isolated system, and it is a measure of uncertainty and disorder of the system. In 1948, Shannon extended the original concept of thermodynamic entropy in the field of information theory and defined information entropy with probability and mathematical statistics as tools. Information entropy represents the degree of uncertainty of a probability distribution.By extension, people substituted the probability distribution function in information entropy with the function of non-probability distribution, which developed various definitions of entropy. In 1958, Kolmogrov defined the measure entropy, called Kolmogrov entropy (also known as information dimension), which is used to measure the degree of chaos or disorder in the operation of a system. Sinai modified it and called it k-s entropy. But the calculation of k-s entropy is very complicated. Crassbreger and Procaccia proposed the concept of correlation dimension [17] in 1983 and defined the concept class of correlation entropy to approximate Kolmogrov entropy [18]. In 1991, Pincus proposed Approximale Entropy (ApEn), which estimates the complexity of a signal sequence. It can quantitatively represent the complexity and irregularity of a signal sequence. The higher the probability that a signal sequence outputs a new pattern, the greater the complexity of the sequence and the corresponding approximate entropy value [19].

Sample Entropy (SampEn) is a new time series complexity test method improved by Richman based on approximate Entropy [20]. It avoids the meaningless self-matching process which results in the deviation of results in the approximate entropy calculation and has less data required. It is characterized by strong anti-noise and interference ability and good consistency within a large parameter value range [21]. Costa etc. proposed multi-scale entropy theory on the basis of sample entropy [22]. It was originally used in the study of the complexity of biological time series to assess the complexity of time series on different scales. Literature [23] introduced the approximate entropy algorithm into the feature extraction of power system fault signals. When applied to the fault signal of a small current grounding system, it can well realize the quantitative extraction of fault signal characteristics under the unfavorable conditions such as short data and small value. Literature [24] adopts harmonic wavelet packet transform to perform multi-scale decomposition for UHF PD signals of GIS. Then the multi-scale energy and multi-scale sample entropy parameters are extracted as characteristic quantities of pattern recognition. The results show that the recognition effect is better than that of real wavelet packets.

Although the above nonlinear dynamic index feature extraction methods can well extract the non-stationary and nonlinear signal features to some extent. But there are still some shortcomings. It is difficult to calculate the fractal dimension of the image, which relies on different application backgrounds. There is no overall comparison and evaluation, and it is mostly limited to the selection and improvement of the differential box dimension. Algorithms for fractal dimension calculation generally have the disadvantages of large calculation errors and fuzzy adaptive ability [25]. When the Lyapunov index is applied to test the instability of the system, the focus of the problem is mainly reflected in the parameter selection of reconstructed phase space and the calculation method of the maximum Lyapunov index, which is not precise or difficult to calculate [26]. Approximate entropy is a statistically biased estimation, and its calculation results are closely associated to parameter selection, which is not conducive to its application in the case of small data sets and noise [27]. The improved sample entropy based on approximate entropy is more suitable for the analysis of complex nonlinear signals. Multi-scale entropy can reflect the system characteristics from the whole and details by calculating the sample entropy under different scale factors. However, multi-scaling of multi-scale entropy is a kind of low-pass filtering and down-sampling operation [28]. The low-pass filter adopts the sliding average, that is, smooth the original sequence through the rectangular window. Some studies have verified that the filtered sequence cannot meet the requirements of the sampling theorem when sampling down. The down sampling operation creates introduce frequency folding. In addition, the rectangular window has a large edge lobe, resulting in a lot of false oscillation components in the high-scale sequence [29], which impacts the calculation of entropy.

## 3. Conclusions

This paper summarizes the methods of feature extraction for monitoring waveform signals of power equipment. They mainly include spectral analysis and nonlinear analysis. For spectral based feature extraction methods, the characteristics, advantages and disadvantages of FFT, STFT, Gabor transform, and wavelet transform are emphatically analyzed. Then the common nonlinear dynamic indexes such as fractal dimension, Lyapunov index, entropy and complexity are summarized. The application status, advantages and disadvantages of them in power equipment monitoring signal analysis are discussed.

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