The Study of Power Quality Analysis by S-transform

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Abstract. Power quality disturbance recognition is the basis of the power quality control. The application of S-transform (ST) and its different improved forms in power quality signal processing and feature extraction are summarized in this paper. After that, the existing disturbance recognition methods based on ST feature extraction are analysed. Finally, on the basis of summarizing the existing research, the prospect of future research is prospected.

1. Introduction
During the transmission of the electric energy electric, the power system is affected by various factors. The waveform of electric energy that reaches the users often distorts, which leads to the decline of power quality. The power quality problems bring serious harm to the power system and electrical equipment [1].

The causes of transient disturbance include internal fault, lightning interference, and switching impulse and so on. The types of transient disturbances mainly include voltage sag, voltage swell, voltage interruption, and transient oscillations and so on. At the same time, there are many kinds of complex disturbances that occur simultaneously in the power system. The common types include harmonic with sag, harmonic with swell, harmonic with transient, sag with transient, flicker with transient and so on [2]. In practical work, the transient disturbances are distinguished from the harmonic, flicker and so on. Automatic identification of the transient disturbances is the premise and foundation of the power quality transient disturbance control, it is also an important part of the construction of smart grid. There are many kinds of complex disturbances which contain characteristics of different types of disturbance signals, the identification difficulty of the complex disturbances is much greater than that of the single disturbances in the process of disturbance signal recognition. Therefore, the identification of disturbance signals with multiple kinds of complex disturbances is a research difficulty in this field. Generally, the process of the power quality disturbance recognition consists 3 steps: signal processing, feature selection and pattern recognition.

2. Methods of Processing and Feature Extraction of Power Quality Signals
Signal processing is the basis of transient disturbance recognition, and the result of the signal processing directly affects the classification results. The time-frequency analysis methods, include short-time Fourier transformation (STFT), Wavelet transform (WT) and S-transform (ST) are widely used in signal processing. At the time that the power quality signal is distorted, the high frequency part of the signal changes violently and the duration is short, so the signal processing method needs a higher time
resolution. While the changes of the low frequency part are relatively slow, and the higher frequency resolution is needed [3].

ST [4] is an extension of STFT and WT, which has good time-frequency analysis capability. The window function width of ST varies with the frequency, so its time-frequency analysis ability is superior to STFT. The frequency resolution of ST can be accurate to 1Hz, so it has better feature extraction ability in frequency domain compared with WT. In addition, ST has good anti-noise ability and is more suitable for signal analysis of actual power system.

Assume \( h(t) \) represents the power quality signal, and the expression of ST is expressed as:

\[
S(\tau, f) = \int_{-\infty}^{\infty} h(t) g(\tau - t, f) e^{-i2\pi ft} dt
\]

And:

\[
g(\tau, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{\tau^2}{2\sigma^2}}
\]

Where \( g(\tau, f) \) represents the Gauss window, and the position of the Gauss window on the time axis is determined by the parameters \( \sigma \). \( \sigma = 1/|f| \) is the factor of window width. Through the window width factor, the window width can be adjusted according to the frequency change to meet the demand of different frequency signals.

The time-frequency analysis capability of ST depends on the Gauss window function, but the resolution of ST at specific frequency is also determined with the determination of the window width factor. In order to further improve the time frequency analysis capability of ST, the generalized ST methods, such as improved Gauss window function [5], compound Gauss window function [6], hyperbolic window function [7] and improved window function [8] are also introduced into the field of disturbance recognition. After comparing the classification accuracy of the ST under different window functions, it is found that the improved window function is helpful to improve the accuracy of classification.

In addition to the use of different window functions, Chinese scholars pay attention to the different requirements of different types of power quality signals to the time-frequency resolution. The pertinent optimization of the generalized ST has been made by using the improved Gauss window function and adjust the window width factor to \( k/|f| \). By changing the window width, it can adapt to different signal analysis needs. Through statistical analysis, Dr. Yi and others [9] take \( k = \sqrt{3} \) to deal with 9 kinds of disturbance signals. The coefficient of the adjusting the width of the window is higher, which improves the characteristic performance of the high frequency disturbance signal. By providing different window width factors to different types of disturbance signals, Dr. Jin obtained more targeted analysis results [10]. The method is further improved by Professor Yang Honggeng [11]. The main frequency components are determined by the FFT spectrum of the disturbance signals. And the type of signal disturbance is preliminarily determined. In this way, the adaptability of the signal processing method is increased. In addition, Li Li and others [12] introduced the incomplete ST into the field of disturbance parameter estimation, which provided a new idea for reducing the amount of operation of ST.

The disturbing signal is transformed from a one-dimensional time series signal to a two-dimensional time-frequency matrix by ST, the two-dimensional time-frequency matrix is called the S matrix (STM). The elements of the STM represent the amplitude of the complex numbers. The ST modular matrix (STMM) is obtained after calculating the modulus of the amplitudes of the complex number in STM. The line of the STMM corresponds to the amplitude of the time points at a specific frequency, and the column of the STMM represents the amplitude of each frequency at a specific time point. The original
wave forms of some single disturbances and complex disturbances, and the contour map of ST are shown in Fig. 1.

(a) The original waveform of normal and the contour map of ST

(b) The original waveform of sag and the contour map of ST

(c) The original waveform of swell and the contour map of ST

(d) The original waveform of interruption and the contour map of ST

(e) The original waveform of flicker and the contour map of ST

(f) The original waveform of oscillatory transient and the contour map of ST
As shown in Fig.1, the contour map of STMM can effectively reflect the time-frequency characteristics of the disturbance signals. After calculating the row and column vectors of STMM, a large number of time-frequency features of disturbance signals for power quality disturbances identification can be obtained. These disturbance features will play an important role in the process of disturbance recognition.

3. Pattern Recognition

The result of ST is a 2D time-frequency matrix, which can clearly show the energy changes of different frequency components at different time points. Therefore, the disturbance signal characteristics can be extracted from the two aspects of the frequency domain and the time domain. Common features include minimum mean-square error of fundamental frequency corresponding amplitude, minimum mean-square error of frequency corresponding to amplitude, and so on. Because the time-frequency matrix of ST is similar to that of the 2D images, the standard template similarity that is often applied to image recognition is also introduced into disturbance recognition [13] in addition to the ordinary time-frequency characteristics and achieved good results. ST and its improved forms have good feature extraction ability and characteristic performance, they have laid a good foundation for the development of disturbance pattern recognition. Decision tree (DT), Fuzzy Rule (FR), Artificial Neural Network (ANN) and Support Vector Machine (SVM) have been applied to the field of disturbance recognition.

By analysing the characteristics of frequency amplitude curve obtained by ST, document [14] constructed a 4 layer DT to identify 10 transient phenomena including two kinds of complex disturbances. In document [15], 12 kinds of transient signals are preliminarily classified by DT according to the frequency characteristics. Then, 12 fuzzy rules are established by 6 characteristics to get the final classification results. By combining the characteristics of DT method and FR method, the complexity of FR is reduced and the efficiency of classifiers is improved. In document [16], by calculating the maximum information gain and the maximum entropy reduction in the transient sample, the classification feature is automatically extracted and the optimal DT is established. In document [17], in order to improve the nonlinear classification ability of DT and control the scale of DT, a 2D combination feature is used instead of a single feature as a basis for classification of decision tree nodes. The best classification scheme of DT is determined by Gini coefficient, and the DT with comprehensive accuracy and optimal structure is obtained by pruning method and applied to transient stability assessment. In addition, DT are also used in FR generation and aided analysis [18]. In document [19],
the Gauss membership function is used to process signals, and 6 features are extracted to generate the fuzzy recognition system. The fuzzy recognition process is further optimized by adaptive fuzzy particle swarm optimization algorithm to improve the recognition efficiency of the fuzzy recognition system. Considering that the noise interference in actual work will affect the distribution of characteristic values and cause classification errors, it is necessary to fully consider the effect of noise interference on the classification effect when designing the classifier based on the above two methods.

The Neural network models, include Back propagation (BP) neural network, radial basis function (RBF) neural network and probabilistic neural network are commonly used in transient identification. The BP neural network [20] has good transient recognition ability, but the structure of BP is complex and the parameters are too more. In addition, the optimization setting of BP neural network is relatively complex and the learning speed is slow, so it can’t meet the requirements of high real-time transient recognition. RBF neural network has faster training speed, and used to classify the transient phenomenon in document [21]. Beside the local approximation advantage of RBF network is used to improve the classification efficiency, the modular structure is used to optimize classifier and the scale of the neural network classifier is controlled. Probabilistic neural network [22] is a parallel neural network based on Bayes classification rule and Parzen window probability density estimation. Probabilistic neural network is characterized by simple learning process, simple structure and high classification efficiency. It is very suitable for disturbance recognition. But Probabilistic neural network has a high space complexity, which is \( o((n+1)d) \). Where \( d \) is the feature vector dimension (input layer neuron number), and \( n \) is the number of training samples (the number of hidden neurons). Therefore, when using probabilistic neural networks to design transient classifier, it is necessary to fully consider the requirements of the specific application environment for the classifier and the performance of the hardware platform (that is, whether the hardware meets the requirements of larger storage space). In addition, the dimension of the feature vector and the number of training samples should be controlled as much as possible in the design process, and the requirement of the classifier to the hardware should be reduced without affecting the classification effect.

SVM can deal with the linear non-separable problems, and there is no local extremum and other defects, and space complexity is low. At the same time, SVM are suitable for less training samples. Dr. Huang applies SVM to power quality data analysis and achieves good results. It is very suitable for transient recognition in small training samples [23].

Due to the excellent time-frequency analysis capability of ST, a large number of researches have been done to combine ST and its improved form with different pattern recognition methods to identify power quality disturbances. Document [23] uses ST and SVM to identify 8 kinds of power quality disturbances including 2 kinds of complex disturbances under different noise environments. The method can maintain the classification accuracy above 95% under the condition of 30dB or above, and the accuracy under 20dB is 87.38%. The document [24] uses FST and DT to identify 12 kinds of power quality disturbances including 6 kinds of compound disturbances and the accuracy of recognition was further improved. The method can maintain the classification accuracy above 98% under the condition of 30dB or above. Document [25], [26] and so on, used various improved forms of ST and combine different pattern recognition methods to identify power quality disturbances, and the recognition accuracy is further improved.

Table 1 shows the results of disturbance recognition using ST and its improved forms combined with different pattern recognition methods in some studies.
Table 1. The application of ST and its improved forms in existing researches

| Literature | Signal Processing | Pattern Recognition | Type of Disturbance Signals | Recognition Accuracy/% |
|------------|------------------|---------------------|-----------------------------|------------------------|
|            |                  |                     | Single | Complex | 20dB | 30dB | 40dB | 50dB |
| [24]       | MST              | ELM                 | 8      | 6       | 96.8 | 99.9 | 100 | —    |
| [25]       | GST              | PNN                 | 6      | —       | 99.28 | 99.38 | 99.28 | 99.44 |
| [26]       | OMFST            | DT                  | 6      | 6       | —    | 98.34 | 99.06 | 99.68 |
| [27]       | ST               | DT                  | 9      | 4       | 96.38 | —    | —    | —    |
| [27]       | ST               | SVM                 | 9      | 4       | 90.46 | —    | —    | —    |
| [28]       | FDST             | DT                  | 6      | 7       | —    | 97.44 | 98.1 | 98.97 |
| [29]       | HMST             | DT                  | 7      | 3       | 94.36 | 97.91 | 99.27 | —    |
| [30]       | ST               | ANN                 | 6      | 3       | 91.04 | 97.51 | 99  | —    |
| [31]       | ST               | FDT                 | 7      | 6       | —    | 97.95 | 98.67 | —    |
| [32]       | FST              | DT                  | 5      | 6       | —    | 95.3 | 98.2 | 99.2 |
| [33]       | ST               | DT                  | 9      | 2       | 94.36 | 97.91 | 99.27 | —    |
| [23]       | ST               | SVM                 | 6      | 2       | 87.38 | 95.50 | 98.75 | 99.75 |

4. Lack of Research and Future Improvement

(1) In signal processing, the improved forms of ST can improve or reduce time resolution or frequency resolution by adjusting relevant parameters, but can’t be achieved simultaneously. The existing research usually determines the relevant parameters by the disturbance type, but doesn't consider the different simultaneous frequency accuracy requirements when the disturbance occurs at different frequency ranges. Therefore, the adaptability of the methods is insufficient. In addition, the related parameters are directly determined by a large number of experimental results and lack of the theoretical basis.

(2) In feature extraction, the features are generally extracted from the time or frequency domain, and the changes of features in the range of different frequency domain are not taken into consideration. The method of distinguishing disturbance signals by image features has not yet received enough attention.

(3) In feature selection, the feature selection in the field of transient disturbance recognition is still in its infancy. The existing research is different because of the analysis of the type of disturbances (especially the type of complex disturbances). The existing feature selection results can’t be applied effectively at the time that the new type of disturbance is identified.

(4) In pattern recognition, the recognition of disturbance types is still not comprehensive enough, especially for the complex disturbance types. The structure of classifier and the optimization of parameter still need to be improved. In particular, the attention should be paid to the efficiency and hardware requirements of training and classification, so as to promote the application of the related fields.

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