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Detection and Classification of Power Quality Disturbances Using S-Transform and Wavelet Algorithm

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Abstract**—**Detection and classification of power quality (PQ) disturbances is an important consideration to electrical utilities and many industrial customers so that diagnosis and mitigation of such disturbance can be implemented quickly. S-transform algorithm and continuous wavelet transforms (CWT) are time-frequency algorithms, and both of them are powerful in detection and classification of PQ disturbances. This paper presents detection and classification of PQ disturbances using S-transform and CWT algorithms. The results of detection and classification, provides that S-transform is more accurate in detection and classification for most PQ disturbance than CWT algorithm, where as CWT algorithm more powerful in detection in some disturbances like notching.

Keywords**—**CWT, Disturbances classification, Disturbances detection, Power quality, S-transform.

I. Introduction

POWER quality has become a very important issue over the last decade in which concerns in fast detection of disturbances has imposed special requirements for PQ monitoring equipment and created a need for sophisticated software to analyze the monitored data. Accurate measurement of power disturbance in real-time circumstance is also important for PQ monitoring and mitigation, protection and control in power systems [1]. This paper presents the detection and classification of PQ disturbances using S-transform and CWT in Matlab code for various types of PQ disturbances such as voltage sag, transient, notching and interruption. Various signal-processing techniques have been applied for detecting and classifying different types of PQ disturbances encountered in power systems. Among them, the most widely used are the fast Fourier transform (FFT) and the short time Fourier transform (STFT) [2].

Both the FFT and STFT techniques are mainly used for analyzing power disturbance signals of stationary in nature but for non-stationary signals, the techniques cannot track the signal dynamics properly because FFT can only show the existence of certain frequency components while STFT is limited to a fixed window width [2]. The alternative algorithms of STFT are the CWT. The CWT is used instead as an alternative approach for analyzing stationary, non-stationary and non-periodic wide band signals because of its ability to focus in short time intervals on the high frequency components and in long time intervals on the low frequency components. CWT leads to accurate frequency resolution and poor time location at low frequency. Reciprocally, the CWT provides accurate time location and bad frequency resolution at high frequency. Such a characteristic is appropriate for detecting signals such as voltage sag and transient overvoltage, a modification of the CWT known as the S-transform. The S-transform is based on a moving and scalable localizing Gaussian window and has characteristics superior to the CWT. It is fully convertible from the time domain to the two-dimensional frequency translation domain and to the familiar Fourier frequency domain. The amplitude-frequency–time spectrum and the phase–frequency–time spectrum are both useful in defining local spectral characteristics. The superior properties of the S-transform are due to the fact that the modulating sinusoids are fixed with respect to the time axis while the localizing scalable Gaussian window dilates and translates. As a result, the phase spectrum is absolute in the sense that it is always referred to the origin of the time axis or the fixed reference point [3]. The S-transform provides a better characterization and feature extraction of PQ disturbances [4].

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II. Continuous Wavelet Transform Theory

CWT approach is more flexible than that of STFT. CWT uses a time-window function that changes with frequency as opposed to the STFT in which the window function is fixed. This adaptive time window function is derived from a prototype function called mother wavelet. The mother wavelet is scaled and translated to provide information in the frequency and time domains, respectively [5].

The continuous wavelet transform can be defined as follows,

$$CWT_X(t,s) = \int_{-\infty}^{\infty} x(\tau)\psi^*_{t,s}(\tau)d \qquad (1)$$

where x (t) is a signal and $\psi_{t,s}(\tau)$ is the wavelet basis function set defined as:

$$\psi_{t,s}(\tau) = \frac{1}{\sqrt{s}}\psi\left(\frac{\tau - t}{s}\right) \qquad (2)$$

where s is the scaling variable (s > 0) given by,

$$s = {}^{fo}\!/\!_{f} \tag{3}$$

where fo is the frequency of the chosen mother wavelet.

The factor $1/\sqrt{s}$ in (2) is a scale-dependent normalization factor, employed so that all the wavelets have the same energy. For large values of s, the window function becomes a stretched version of the mother wavelet. Therefore, large values of s provide a broad time-width windowing function located in the low frequency region of the frequency domain. On the other hand, small values of s provide a narrow time-width windowing function located in the high-frequency region of the frequency domain. By substituting (2) into (1), and integrating it, the CWT becomes,

$$\mathrm{CWT}_x(t,s) = \sqrt{s}\int_{-\infty}^{\infty} X(f')\psi^*[s(f'-f)]e^{i2\pi f't}df' \tag{4}$$

CWT has a filter-bank interpretation in which each wavelet basis function can be thought of as a filter through which the original signal is passed. Each filter, however, has a fixed relative bandwidth as opposed to the fixed absolute bandwidth of STFT [5].

III. S-Transform Theory

The S-transform produces a time-frequency representation of a time series signal by uniquely combining a frequency-dependent resolution that simultaneously localizes the real and imaginary spectra. The basis function for the S-transform is the Gaussian modulated cosinusoid, so that it is possible to use intuitive notions of cosinusoidal frequencies in interpreting and exploiting the resulting time-frequency spectrum. With the advantage of fast lossless invariability from time domain to time-frequency domain, and back to the time domain, the usage of the S-transform is very analogous to the Fourier transform. In the case of non-stationary disturbances with noisy data, the S-transform provides patterns that closely resemble the disturbance type and, thus, requires a simple classification procedure. Furthermore, the S-transform can be derived from the CWT by choosing a specific mother wavelet and multiplying a phase correction factor. Thus, the S-transform can be interpreted as a phase-corrected CWT [6]. The S–transform generates contours which are suitable for classification by simple visual inspection unlike the CWT that requires specific methods like standard multi resolution analysis [7]. By using a simple rule base or a neural network along with the features extracted from the S–transform contours, one can easily dispense with the visual inspection procedure of the S-transform.

To derive the S-transform from the CWT [7], firstly, the $CWT(\tau,d)$ of a function $x(t)$ is defined as,

$$CWT(\tau,d) = \int_{-\infty}^{\infty} x(t)w(t-\tau,d)dt \tag{5}$$

where,

$w(t,d)$: mother wavelet

d : scale which is the inverse of f

The S-transform is obtained by multiplying the $CWT(\tau,d)$ with a phase factor, which is expressed as,

$$S(\tau,f) = CWT(\tau,d)e^{i2\pi f\tau} \tag{6}$$

Substituting (5) into (6), the S-transform becomes,

$$S(\tau,f) = \int_{-\infty}^{\infty} x(t)w(t-\tau,d)e^{i2\pi f\tau}dt \tag{7}$$

The mother wavelet for this particular case is defined as,

$$w(t,f) = g(t)e^{-i2\pi ft} \tag{8}$$

where,

$g(t)$: Gaussian window given as,

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}}e^{-t^2/2\sigma^2} \tag{9}$$

σ is the Gaussian window width which is given by,

$$\sigma(f) = T = \frac{1}{|f|} \tag{10}$$

Substituting (9) and (10) into (8), we get,

$$w(t,f) = \frac{|f|}{\sqrt{2\pi}}e^{-t^2f^2/2}e^{-i2\pi ft} \tag{11}$$

Substituting (11) into (7), the final S-transform equation becomes,

$$S(\tau,f) = \frac{|f|}{\sqrt{2\pi}}\int_{-\infty}^{\infty} x(t)e^{-(t-\tau)^2f^2/2}e^{-i2\pi ft}dt \tag{12}$$

The S-transform distinguishes itself from the many time-frequency representations by combining progressive resolution with absolutely referenced phase information. Daubechies has stated that progressive resolution gives a fundamentally sounder time-frequency representation [8]. In this case, the term referenced phase means that the phase information given by the S-transform is always referenced to time t = 0, which is also true for the phase given by the Fourier transform. This is different from the CWT where the phase of the wavelet transform is relative to the center (in time) of the analyzing wavelet. Thus, as the wavelet translates, the reference point of the phase translates [9].

The S-transform has some unique properties in which it uniquely combines frequency dependent resolution with absolutely reference phase so that the time average of the S-transform equals the Fourier spectrum. It simultaneously estimates the local amplitude spectrum and the local phase spectrum, whereas the wavelet approach is only capable of probing the local amplitude and power spectrum. The S-transform can independently probe the positive and the negative frequency spectra whereas many wavelet approaches are incapable of being applied to a complex time series. It is sampled at the discrete Fourier transform frequencies unlike the CWT where the sampling is random [9].

A. PQ disturbances Detection Using S-transform and CWT

The analysis of PQ disturbances using both algorithms S-transform and CWT, shows that S-transform more accurate than wavelet except notching disturbances where CWT is better than S-transform. Fig. 1 up to Fig. 5 shows the results of analysis.

B. PQ disturbances Classification Using S-transform and CWT

Based on coefficients, CWT used to classify the PQ disturbances which are relatively many disturbances not classified correctly. S-transform is more reliable for PQ classification than CWT. To use S-transform for PQ classification, feature is extracted from the contour result [10]. Feature extraction is a preprocessing operation that transforms a pattern from its original form to a new form suitable for further processing. The first step in performing feature extraction process is by mapping the data of a distorted signal into its S-transform domain. For non-stationary disturbances with noisy data, the S-transform provides patterns that closely resemble the disturbance type. Features of the disturbance signals are extracted from the S-transform analysis in terms of TFR curve which is in the form of contour. The features extracted from the S-transform analysis are then used to formulate rules for the simple rule based system developed for classifying the PQ disturbances. Table I shows the features extracted from S-transform analysis.

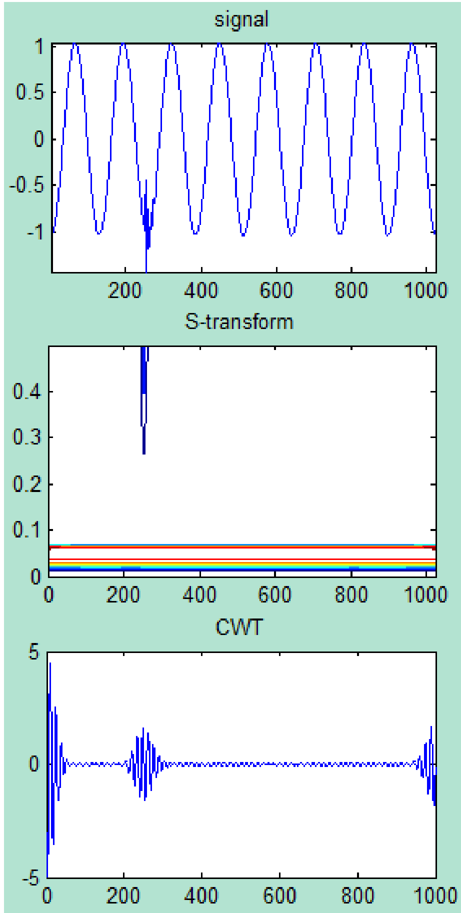

Fig. 1 Transient disturbance detection using S-transform and CWT

TABLE I
FEATURES EXTRACTED FROM THE S-TRANSFORM ANALYSIS

Feature	Description
F1	Amplitude factor obtained using S-transform
F2	The difference between maximum values of clear and distorted signals
F3	Mean value of S-transform of clean signal
F4	S-transform absolute value of the frequency of the largest amplitude of each time step

TABLE II
DATABASE PQ DISTURBANCE WAVEFORMS

Type of PQ disturbance	Number of waveforms
Voltage Sag	100
Notching	115
Impulsive Transient	100
Interruption	100
Clean Signal	100

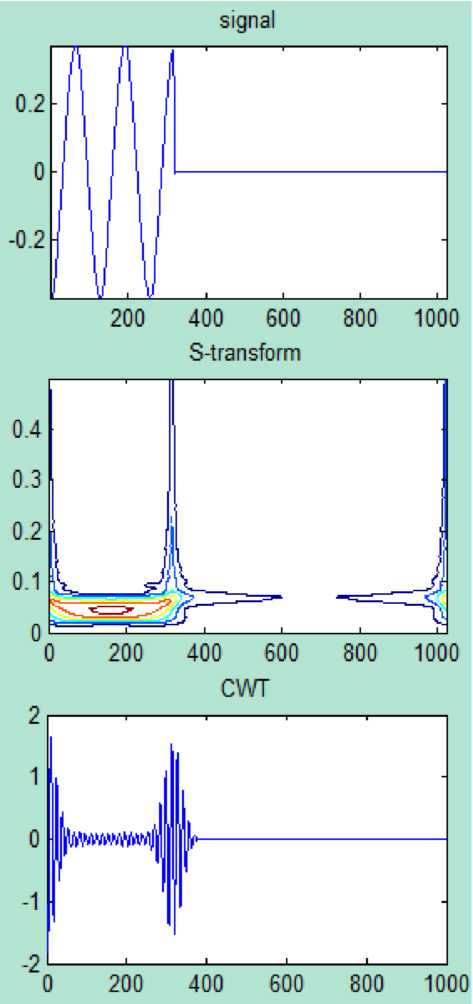

Fig. 2 Interruption disturbance detection using S-transform and CWT

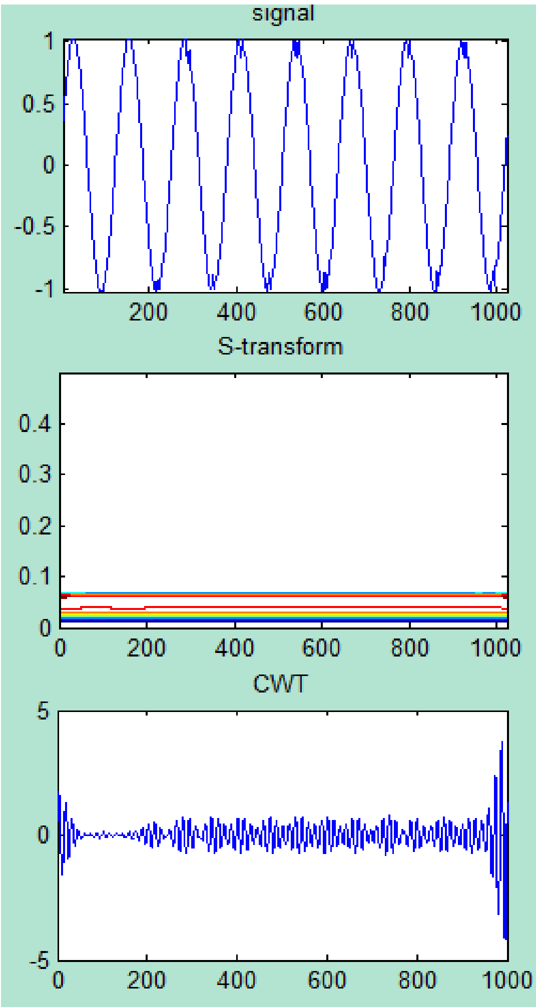

Fig. 3 Notching disturbance detection using S-transform and CWT

C. Preparation of Experimental Data

To avoid having some feature components with large dynamic range dominating other small feature components, normalization of data is applied. In the PQ database, 515 disturbance waveforms were stored in which the data was obtained from PQ monitoring carried out by the utility. Various types of PQ disturbances in the database are shown in Table II.

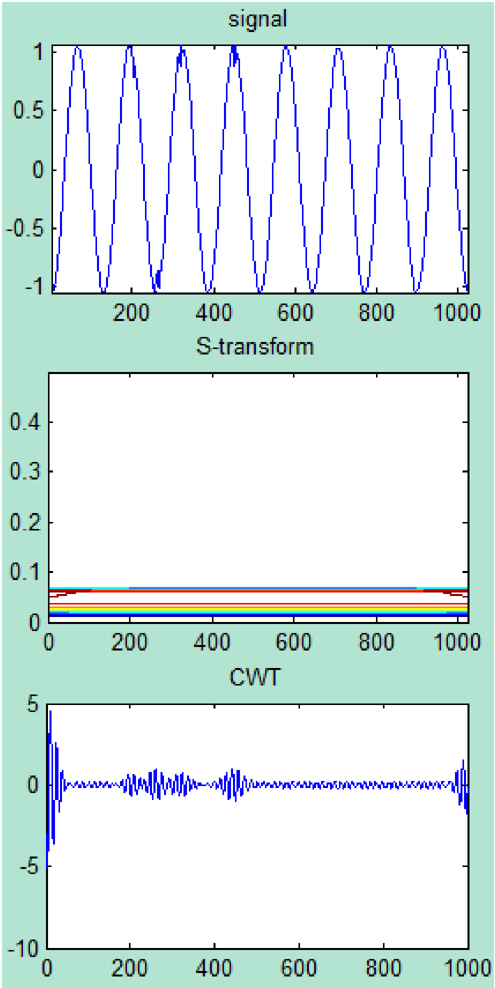

Fig. 4 Notching disturbance detection using S-transform and CWT

III. PQ Disturbance Classification Results

To validate the proposed rule based expert system, it has been tested with 515 samples of disturbance data collected from utility PQ monitoring. Table III shows the PQ disturbance classification results in which the average percentage of correct classification for all events is 98.2%. From the table, it is noted that notching disturbance is relatively difficult to classified using S-transform. From the results, it can be concluded that accurate disturbance classification can be obtained, in which only nine disturbances are incorrectly classified, while all the other disturbances are correctly classified.

TABLE III
PQ Disturbance Classification Results

Power Quality Event Type	Total no. of data sets	Testing Data No. of Data Correctly Classified	No. of Data Incorrectly Classified	% Correct classificatio n
Voltage Sag	100	97	3	97
Notching	115	109	6	94.7
Transient	100	100	0	100
Interruption	100	100	0	100
Clean Signal	100	100	0	100
Total Events	515	506	9	98.2

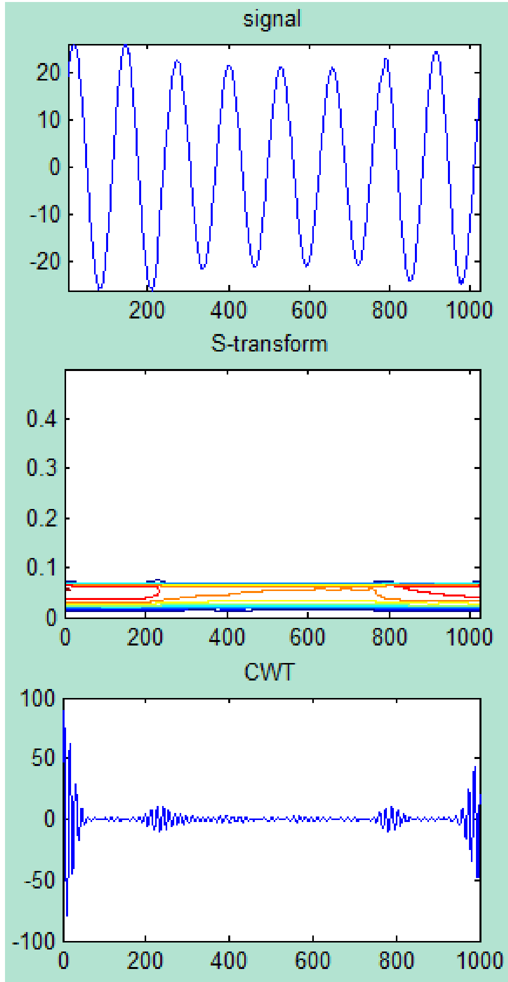

Fig. 5 Sag disturbance detection using S-transform and CWT

IV. Conclusion

Detection and classification of various PQ disturbances using S-transform and CWT has been analysis. CWT is shows better detection in some disturbance and S-transform is powerful in both detection and classification with weakness in some disturbance. Using the S-transform algorithm, the features of disturbances were extracted and then used in the PQ classification. 515 samples of disturbances obtained from utility PQ monitoring were used for validating the effectiveness classifying the PQ disturbances. The average percentage of correct classification for classifying 515 events is 98.2%.

References

[1] T. Lin, and A. Domijan, “Real time Measurement of Power Disturbances Part 1. Survey and a Novel Complex Filter Approach”, Electric Power Systems Research, Elsevier, Science Direct, 76, pp. 1027-1032. 2006.

[2] A. Moussa, M.El-Gammal, E. Abdallah, and A. El-SLoud, “Hardware - software structure for on-line power quality assessment”, in Proc of the 2004 ASME/IEEE Joint, 2004, April 6-8, pp.147 – 152.

[3] R. G. Stockwell, L. Mansinha, and R. P. Lowe, “Localization of the Complex spectrum: The S-Transform”, IEEE Trans. On Signal Processing, vol. 144, no. 4, pp. 998 – 1001. 1996.

[4] M. V. Chilukuri, and P. K. Dash, "Multiresolution S-Transform-Based Fuzzy Recognition System for Power Quality Events", IEEE Transactions on Power Delivery 19 1, pp. 323 – 330. 2004.
[5] Alexander D. Poularikas. 2000. The Transforms and applications Handbook, 2nd Ed. Boca Raton, Florida: CCR press LLC.
[6] I. W. C. Lee, and P. K. Dash, "S-Transform Based Intelligent System for Classification of Power Quality Disturbance Signals". IEEE Transactions on Power Delivery 18(2): 800-805. 2003.
[7] B. R. Jaya, K. Dusmanta and B. M. Karan, "Power System Disturbance Recognition Using Wavelet and S-Transform Techniques", International Journal of Emerging Electric Power Systems, 1(2). Article 1007. 2004.
[8] I. Daubechies, "The wavelet transforms, time-frequency localization and signal analysis", IEEE Transactions Information Theory 36(5): 961-1005. 1990.
[9] R. G. Stockwell, "A basis for efficient representation of the S-transform", Journal of Digital Signal Processing, Elsevier INC: 371-393. 2006.
[10] M. E. Salem Abozaed, A. Mohamed and S. Abdul Samad, "Rule based system for power quality disturbance classification incorporating S-transform features" Expert Systems with Applications Journal, Elsevier, 37 (2010) 3229–3235.

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