Multiresolution S-Transform-Based Fuzzy Recognition System for Power Quality Events

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***Abstract*—The paper proposes a novel fuzzy pattern recognition system for power quality disturbances. It is a two-stage system in which a mulitersolution S-transform is used to generate a set of optimal feature vectors in the first stage. The multiresolution S-transform is based on a variable width analysis window, which changes with frequency according to a user-defined function. Thus, the resolution in time or the related resolution in frequency is a general function of the frequency and two parameters, which can be chosen according to signal characteristics. The multiresolution S-transform can be seen either as a phase-corrected version of the wavelet transform or a variable window short time Fourier transform that simultaneously localizes both real and imaginary spectra of the signal. The features obtained from S-transform analysis of the power quality disturbance signals are much more amenable for pattern recognition purposes unlike the currently available wavelet transform techniques. In stage two, a fuzzy logic-based pattern recognition system is used to classify the various disturbance waveforms generated due to power quality violations. The fuzzy approach is found to be very simple and classification accuracy is more than 98% in most cases of power quality disturbances.**

***Index Terms*—Fuzzy logic, multiresolution analysis, pattern recognition, power quality, S-transform, short time Fourier transform, variable window, wavelet transform.**

I. Introduction

THE quality of electric power has become an increasing concern for electric utilities and their customers over the last decade. Poor quality is attributed due to the various power line disturbances like voltage sag, swell, impulsive, and oscillatory transients, multiple notches, momentary interruptions, harmonics, and voltage flicker, etc. In order to improve the quality of electrical power, it is customary to continuously record the disturbance waveforms using power-monitoring instruments. Unfortunately, most of these recorders rely on visual inspection of data record creating an unprecedented volume of data to be inspected by engineers.

The Fourier transform (FT) [1] has been used as an analyzing tool for extracting the frequency contents of the recorded signals. However, due to constant bandwidth, the FT is not an efficient technique for capturing short-term transients like impulses and oscillatory transients in a power system.

Also, the time-evolving effects of the frequency in nonstationary signals have not been considered in FT analysis. Although the short time Fourier transform (STFT) can partly alleviate the problem, it has the limitation of fixed window width chosen *apriori* and this imposes limitations for the analysis of low-frequency and high-frequency nonstationary signals at the same time. In contrast to Fourier transform-based technologies, the wavelet transform [2]–[7] uses short windows at high frequencies and long windows at low frequencies; thus closely monitoring the characteristics of nonstationary signals. These characteristics of the wavelet transform provide an automated detection, localization, and classification of power quality disturbance waveforms.

Although wavelet multiresolution analysis combined with a large number of neural networks provides efficient classification of power quality (PQ) events, the time-domain featured disturbances, such as sags, swells, etc. may not easily be classified [8], [9]. In addition, if an important disturbance frequency component is not precisely extracted by the wavelet transform, which consists of octave band-pass filters, the classification accuracy may also be limited. This paper, therefore, presents a generalized S-transform derived from STFT [10] for the detection, localization of PQ disturbance signals. The S-transform is essentially a variable window STFT whose window width varies inversely with the frequency. The S-transform produces a time-frequency representation of a time varying signal by uniquely combining the frequency dependent resolution with simultaneously localizing the real and imaginary spectra. The S-transform is similar to the wavelet transform but with a phase correction and here both the amplitude and phase spectrum of the signal are obtained. Since the S-transform provides the local spectrum of a signal, the time averaging of the local spectrum gives the Fourier transform. The S-transform of a PQ disturbance signal provides contours, which closely resemble the disturbance pattern unlike the wavelet transform, and hence, the features extracted from it are very suitable for developing highly efficient and accurate classification scheme. Further, the S-transform analysis of time varying signal yields all of the quantifiable parameters for localization, detection, and quantification of the signal. This paper also presents the design of a simple fuzzy-based classification scheme using the features from the S-transform and the classification accuracy is very high even in the presence of random noise. Several simulated PQ waveforms are tested using this new classifier.

II. Multiresolution S-Transform

The Fourier transform of a time varying signal $h(t)$ is given by

$$H(f) = \int_{-\infty}^{\infty} h(t) e^{-i2\pi f t} dt. \tag{1}$$

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The spectrum $H(f)$ is referred to as the "time-averaged spectrum." If the signal $h(t)$ is multiplied point by point with window function $g(t)$, then the resulting spectrum is

$$H(f) = \int_{-\infty}^{\infty} h(t) g(t) e^{-i2\pi f t} dt. \tag{2}$$

The S-transform is obtained by defining a particular window function in the form of a normalized Gaussian as

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(t^2/2\sigma^2)} \tag{3}$$

and then allowing the Gaussian to be a function of translation τ and dilation (window width) σ. The window width σ is made proportional to the inverse of frequency and is chosen as

$$\sigma(f) = \frac{1}{a + b|f|}. \tag{4}$$

If $a = 0$, $\sigma(f) =$ denotes S-transform and for $b = 0$, $\sigma(f)$ denotes a STFT. A typical value of b varies between 0.333 to 5, giving different frequency resolutions. For low frequencies, a higher value of b is chosen and for high frequencies, lower value of b is chosen to provide suitable frequency resolutions.

The FT of the window function $g(t)$ is obtained as

$$G(v) = e^{-2\pi\sigma^2 v^2} = e^{-2\pi v^2 \left(\frac{1}{a+b|f|}\right)^2}. \tag{5}$$

S-transform produces a multiresolution analysis like a bank of filters with a constant relative bandwidth (constant Q analysis). The analysis window $w(t, f)$ is Gaussian and

$$\int_{-\infty}^{\infty} g(t, f) dt = 1. \tag{6}$$

Therefore

$$\int_{-\infty}^{\infty} h(t) S(t, f) d\tau = H(f). \tag{7}$$

Substituting (3) and (4) in (2), we get the S-transform of $h(t)$ as

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) g(\tau - t, f) e^{-i2\pi f t} dt. \tag{8}$$

Since $S(\tau, f)$ is complex, it can also be written as

$$S(\tau, f) = A(\tau, f) e^{i\varphi(\tau, f)} \tag{9}$$

where $A(\tau, f)$ is amplitude S-spectrum and $\varphi(\tau, f)$ is the phase S-spectrum. It can be noted that the S-transform improves the STFT in that it has a better resolution in phase space (i.e., a more narrow time window for higher frequencies) giving a fundamentally more sound time frequency representation. The discrete version of the S-transform is calculated by taking the advantage of the efficiency of the fast Fourier transform (FFT) and the convolution theorem. The discrete Fourier transform of the sampled signal $h(kT)$, $k = 0, 1, N-1$ is

$$H\left[\frac{n}{NT}\right] = \frac{1}{N} \sum_{k=0}^{N-1} h(kT) e^{-i(2\pi nk/N)} \tag{10}$$

and discrete version of the S-transform of $h(kT)$ is obtained as (by letting $f \to n/NT$ and $\tau \to jT$)

$$S\left(jT, \frac{n}{NT}\right) = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] G(m, n) e^{i\frac{2\pi mj}{N}} \tag{11}$$

where

$$G(m, n) = e^{-(2\pi^2 m^2 \alpha^2 / n^2)} \tag{12}$$

$\alpha = 1/b$, j, m, and $n = 0, 1, 2, \ldots, N-1$, and $N =$ total number of samples.

The discrete inverse of S-transform is obtained as

$$h(kT) = \frac{1}{N} \sum_{n=0}^{N-1} \left\{ \sum_{j=0}^{N-1} S\left[\frac{n}{NT}, jT\right] \right\} e^{i(2\pi nk/N)}. \tag{13}$$

The computation of the multiresolution S-transform is very efficient using convolution theorem and FFT. The computational steps are outlined as follows.

1) Denote n/NT, m/NT, kT, and jT as n, m, k, and j, respectively, for all of the computations.
2) Obtain discrete Fourier transform $H[m]$ of the original time-varying signal $h[k]$, with N points and sample interval T, using FFT routine from (10).
3) Compute the localizing Gaussian $G[n, m]$ for the required frequency n using (12).
4) Shift the spectrum $H[m]$ to $H[m+n]$ for the frequency n by using convolution theorem.
5) Determine $B(n, m) = H(m+n) \cdot G(m+n)$.
6) Compute inverse Fourier transform of $B(n, m)$ from m to j to give the row of $S[n, j]$ corresponding to the frequency n.
7) Repeat steps 3, 4, and 5 until all of the rows of $S[n, j]$ corresponding to all discrete frequencies n have been obtained.

The total number of operations for computing S-transform is $N(N + \mathrm{NlogN})$.

The multiresolution S-transform output is a complex matrix, the rows of which are the frequencies and the columns are the time values. Each column thus represents the "local spectrum" for that point in time. Also, frequency-time contours having the same amplitude spectrum are obtained to detect, and localize power disturbance events. A mesh three-dimensional (3-D) of the S-transform output yields frequency-time, amplitude-time, and frequency-amplitude plots. The original software code developed by Stockwell [10] in Matlab has been modified by the authors for power quality waveform studies.

To illustrate the use of multiresolution S-transform for nonstationary signal analysis, a 50% voltage sag of three-cycles duration is created for a pure sinusoidal voltage waveform in a data window of eight cycles (using a sampling rate of 32 samples/cycle). The time-frequency contours and 3-D mesh for the signal shown in Fig. 1(a) are shown in Fig. 1(b) and (c), respectively. From the 3-D plot, one can find the magnitude, frequency, and time informations to detect, localize, and visually classify the event. Also, it is observed that the increase or decrease of the signal magnitude can be deduced from the innermost (or the

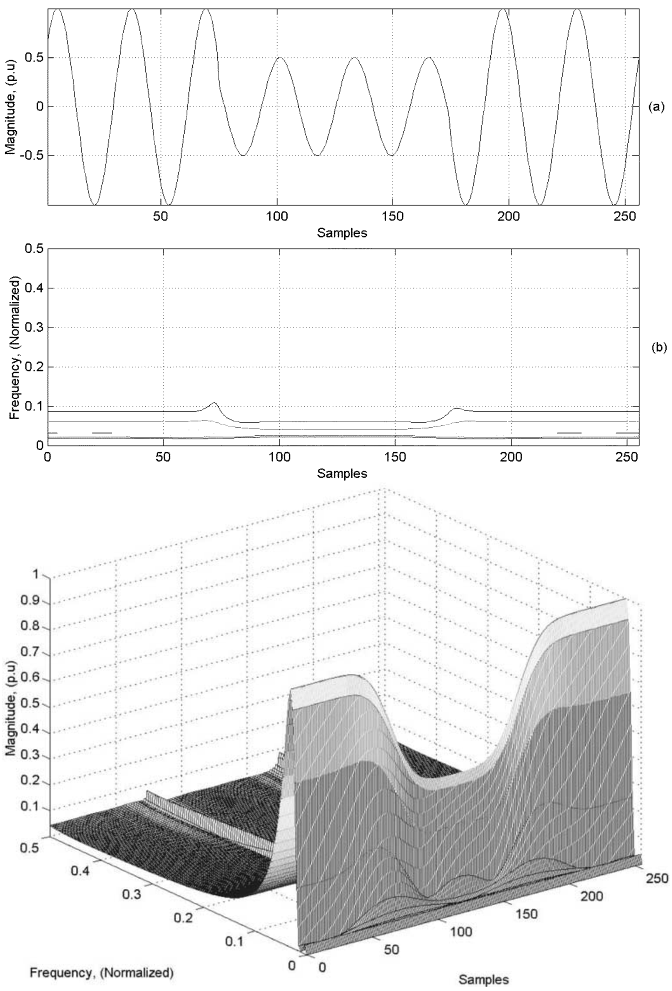

Fig. 1. (a) Fifty-percent voltage sag. (b) S-transform contours of 50% voltage sag. (c) 3-D S-transform plot of 50% voltage sag.

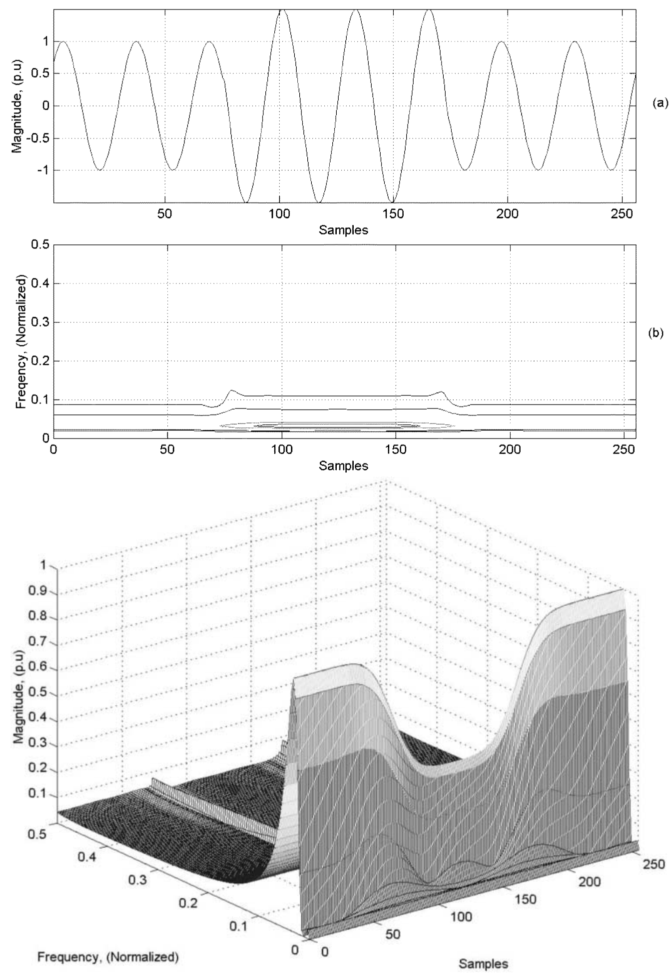

Fig. 2. (a) Fifty-percent voltage swell. (b) S-transform contours of 50% voltage swell. (c) 3-D S-transform plot of 50% voltage swell.

lowest level) contour. Similar plots are shown for three-cycle duration voltage swell in a pure sinusoidal voltage waveform in Fig. 2. In all of the plots, the frequency magnitude (f) is normalized with respect to the sampling frequency (f_s) and is given by f/f_s. From these results, it is quite obvious that in case of S-transform output, one can detect, localize, and quantify the disturbance completely. However, the wavelet transform alone cannot give all of the information which is extracted from the S-transform and requires the use of Fourier transform [8], [9] for quantifications of the signal magnitude, total harmonic distortions, etc.

III. S-Transform Analysis of PQ Events

The various power quality disturbance signals considered for the S-transform analysis are voltage sag, swell, interruption, oscillatory transients, spike (single and multiple), notch (single and multiple). These signals are simulated using Matlab code and are mixed with random white noise of zero mean having signal to noise ratio (SNR) varying from 50 to 20 dB. For a typical noise of $\mathrm{SNR} = 30$ dB, the peak noise magnitude is 3.5% of the peak signal magnitude. The sampling frequency of 1.6 kHz is chosen for the PQ event analysis in this paper. Figs. 3–10 show the time-frequency contours of some of the typical PQ disturbances (sag, swell, transient, spike, and notch) and these contours clearly reveal the nature of the disturbances in the presence of noise. For example, Fig. 3(a) presents the actual signal showing nearly three-cycles voltage sag. In Fig. 3(b), the normalized time-frequency contour obtained from S-transform is shown. This contour gives the maximum output of the normalized frequency-time graph, although other contours are generated showing the pattern of a contour magnitude reduction during voltage sag. Fig. 3(c) gives the magnitude-time spectrum obtained by searching rows of S-transform matrix.

This figure clearly shows the voltage sag amplitude and the time of its occurrence. In Fig. 3(d), the normalized frequency-time plot is shown, which gives the maximum frequency content of the voltage signal shown in Fig. 3(a). Figs. 3–10(a)–(d) show similar plots as in Fig. 3 obtained from the S-transform analysis. The time-frequency contours of the S-transform output shows a decrease or increase in magnitude for voltage sag and swell, and multiple high-frequency contours in case of transients, which provide a better visual classification strategy in comparison to the wavelet transform (similar to time versus rms or peak value of voltage). The magnitude versus time graph in Figs. 3–5 quantify the sag, swell, and interruption. In all other cases like notches, voltage, and oscillatory transients, etc., there is either a fall or rise from

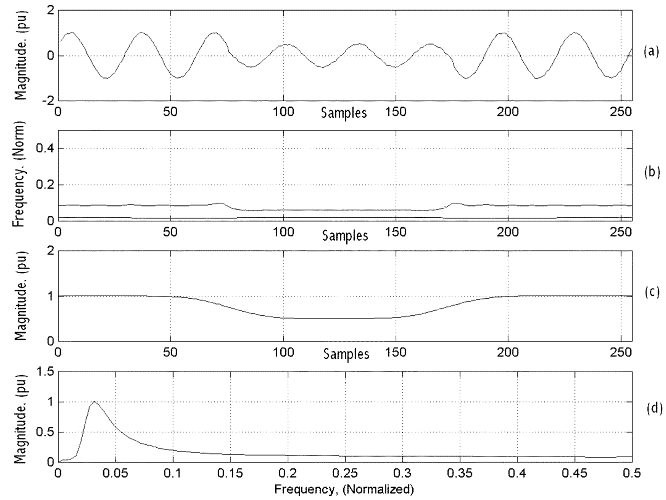

Fig. 3. Voltage sag.

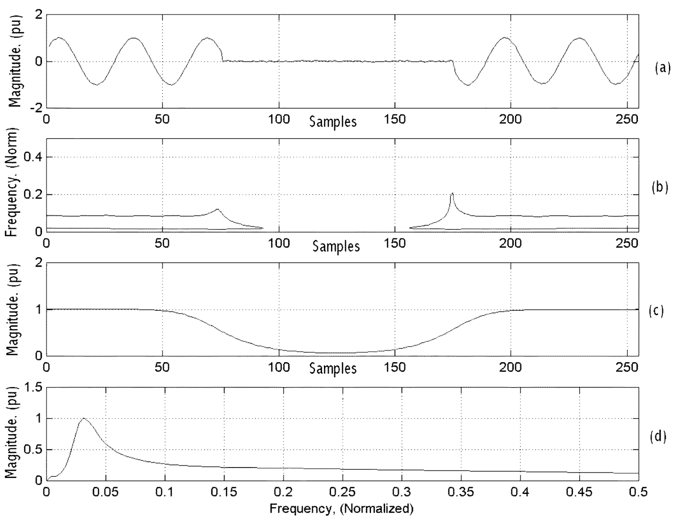

Fig. 4. Voltage interruption.

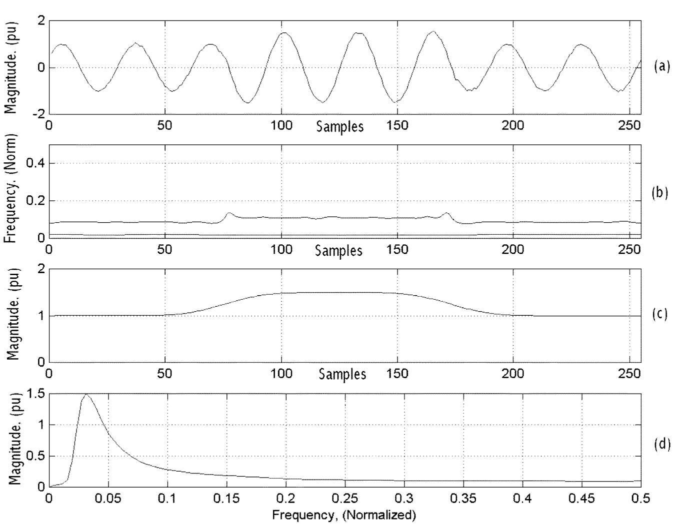

Fig. 5. Voltage swell.

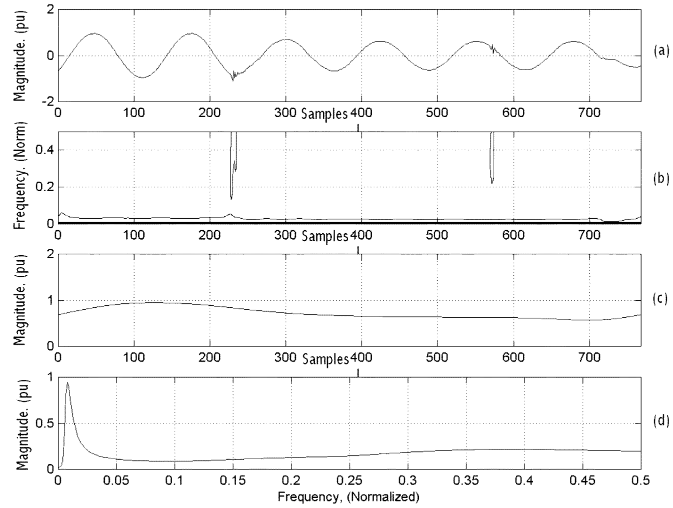

Fig. 6. Voltage transient.

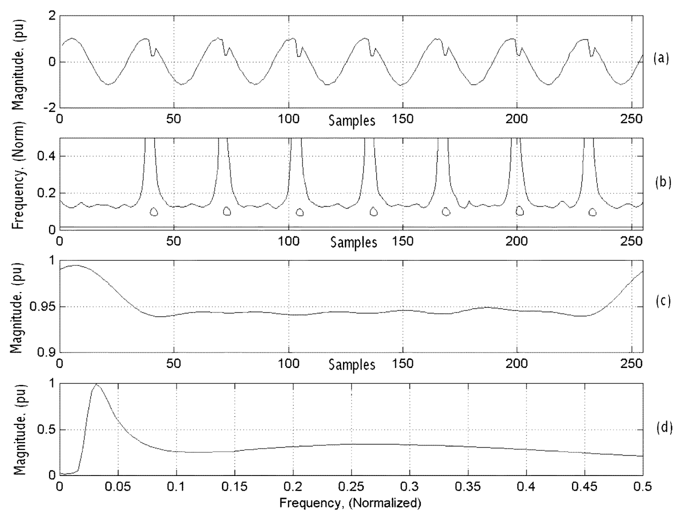

Fig. 7. Multiple notches.

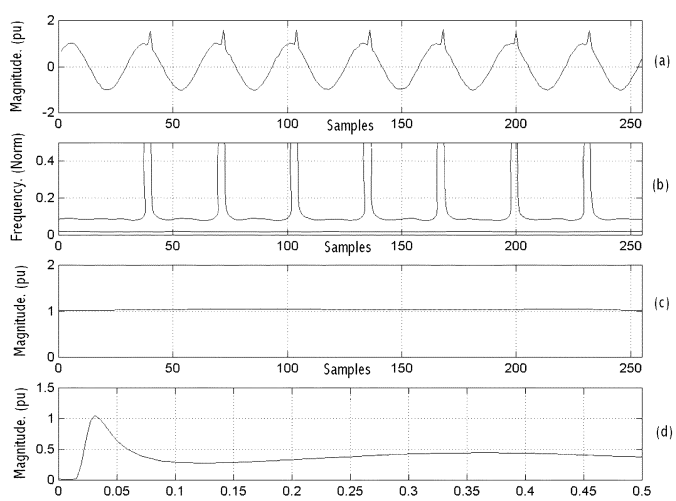

Fig. 8. Voltage spike.

the normal value in the magnitude versus time graph (graph c of Figs. 6, 7, and 10). In analyzing oscillatory transients, voltage impulses, etc., it will be useful to get S-transform output for another window width $(\alpha = 3)$. component in the

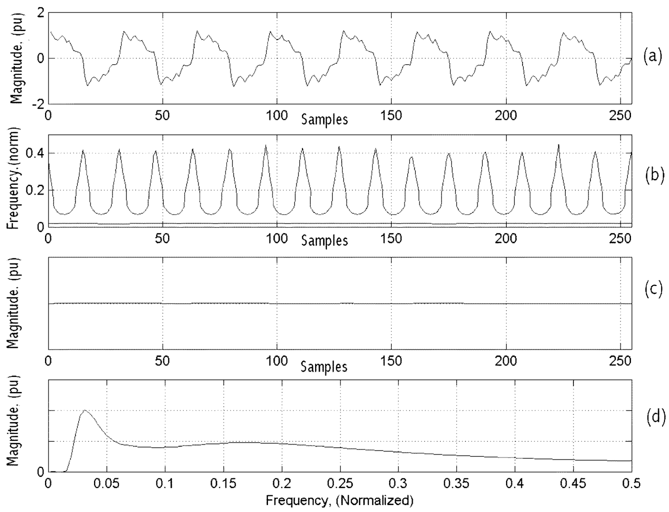

Fig. 9. Voltage harmonics.

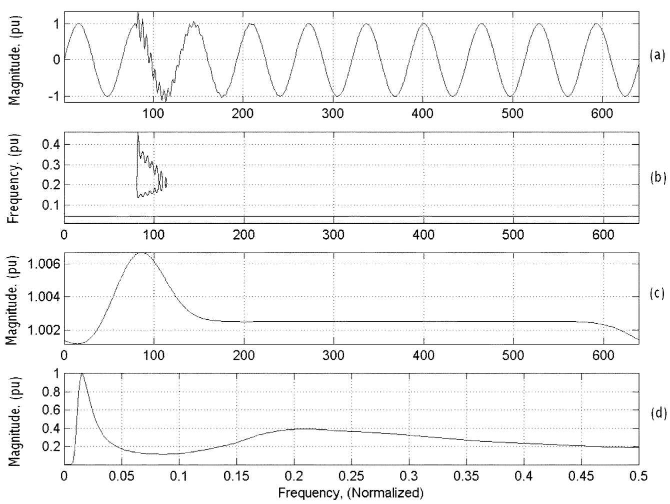

Fig. 10. Switching transient.

power quality disturbance waveform. The S-transform output at different frequency resolutions will be required for classification of high-frequency transients, impulses, notches, etc., since it yields some more parameters for discriminating various types of transient disturbances. It is observed that the standard deviation of second contour at $\alpha = 3$ is an important parameter to distinguish between transients, impulses, and notches.

IV. PQ Disturbance Recognition System

Power quality disturbance recognition is a difficult problem, because it involves a broad range of disturbance categories and varying degree of irregularities. Description of PQ events considered for recognition is outlined in Section III. The generalized S-transform generates the time frequency contours, which clearly display the disturbance pattern for visual inspection. These contours provide features, which can be used by a fuzzy logic or neural network-based pattern recognition systems for classifying these disturbance frequency regions for amplitude frequency and amplitude time plots.

The following important features are used for pattern classification:

1) The standard deviation $\sigma_1 = \mathrm{std}(c_1)$ with $\alpha = 0.2$
2) $\sigma_2 = \mathrm{std}(c_2)$, $\sigma_3 = \mathrm{std}(c_3)$ with $\alpha = 3$ where σ_1, σ_2, σ_3 are standard deviations of contours 1, 2, 3 designated as c_1, c_2, c_3, respectively.
3) An amplitude factor β is obtained as

$$\beta = A_1 + A_2 - B_1 - B_2 \tag{14}$$

where

A_1 max (max (abs(s))) with PQD;
A_2 min (max (abs(s'))) with PQD;
B_1 max (max (abs(s))) with no PQD;
B_2 min (max (abs(s'))) with no PQD;
PQD power quality disturbance;
s S-transform matrix (complex);
s' transpose of S-transform matrix.

4) F_i = instant of occurrence of the disturbance (obtained from the first peak of the time-frequency contour c_1);
5) F_d = duration of occurrence of the disturbance (duration between two peaks of contour c_1).

The standard deviations of the time-frequency representations of the signal in the form of contours can be considered as a measure of the energy for a signal with zero mean. Instead of taking all of the contours to give overall measure of standard deviation, only the most significant contour (c_1) is chosen for classification of the disturbance in this paper. The amplitude factor (β) provides the accurate quantification of signal magnitudes during short-duration steady-state power frequency disturbance events. However, this factor is also very significant as it is able to distinguish transient events, steady state events, and harmonic distortions. To illustrate the relative values of these features, several typical PQ events like voltage sag, swell, interruption, transients, spike, notch, etc., are simulated using Matlab code and a random noise level of 3.5% of the signal is added to all of these disturbances. Table I shows the features at two different window widths ($b = 0.33$ and $b = 5$).

The features described in Table I are used to convert the visual recognition of these time graphs to an automated pattern recognition system by using fuzzy logic or neural network approach. From the table, it is quite obvious that for low-frequency and power frequency steady state disturbances (voltage sag, swell, interruption, and harmonics) σ_1, σ_2 are small and less than 0.05. In case of oscillatory transients, both σ_1, $\sigma_2 \mathrm{are} > 0.1$, where as in case of spikes and notches $\sigma_1 > 0.1$ and $\sigma_2 < 0.05$. The amplitude factor β clearly distinguishes steady state power frequency voltage disturbances and harmonics from the transients in that its value quantifies the type of disturbance. For example, for voltage sag of 10% in the presence of 30 dB noise, $\beta = -0.095$ and for 90% sag, $\beta = -0.891$. With noise level of 40 dB, $\beta = -0.1$, for 10% sag and $\beta = -0.9$ for 90% sag. Similarly, for voltage swell of 90% $\beta = 0.887$ and for 10% swell $\beta = 0.091$. After analyzing these features, an automated disturbance recognition system is presented below.

V. Fuzzy Recognition of Power Quality Events

Although the neural network classifiers for PQ event recognition have been extensively studied by several researchers, the fuzzy logic-based recognition scheme offers a very simple

TABLE I
MULTIRESOLUTION S-TRANSFORM FEATURES FOR FUZZY RECOGNITION SYSTEM

Power Quality Disturbance	Window Size b = 5			Window Size b = 0.333	
Type	σ_1	σ_2	β	σ_2	σ_3
Voltage Sag	0.0218	0.0096	- 0.4630	0.0023	0.0014
Interruption	0.0373	0.0193	- 0.9270	0.0103	0.0066
Swell	0.0452	0.0250	- 0.7060	0.0069	0.0050
Multiple Notch	0.1412	0.1461	- 0.0690	0.0863	0.0058
Single Notch	0.1242	0.0196	- 0.0390	0.0071	0.0059
Spike	0.1486	0.0204	0.0460	0.0060	0.0040
Harmonics	0.1200	0.0686	-0.0120	0.0578	0.0040
10% Sag	0.0329	0.0190	- 0.0950	0.0071	0.0059
90% Sag	0.0358	0.0192	- 0.8910	0.0098	0.0064
10% Swell	0.0348	0.0203	0.0910	0.0060	0.0041
90% Swell	0.0623	0.0267	0.8870	0.0072	0.0053
Transient	0.1051	0.1375	- 0.4820	0.1114	0.0013
Switching Transient1	0.1302	0.0774	0.0738	0.0663	0.0409
Switching Transient2	0.1322	0.00986	0.0078	0.0539	0.0021

but accurate classification strategy of the PQ events unlike the wavelet-based neural classifier (12 neural networks are used) [6] or fuzzy neural classifiers [7] (180 rules are used), the S-transform-based fuzzy classifier is constructed with just 15 to 20 rules. The trapezoidal membership functions are used to fuzzifying the features σ_1, σ_2 (or σ_3) and β. Figs. 11–13 show the fuzzy sets A_1, A_2, A_3, B_1, B_2, B_3, B_4, and B_5 for the above features. The following fuzzy rule base is used:

R1: If σ_1 is A_2 and β is B_3, then WF = NOTCH;
R2: If σ_1 is A_2 and β is B_4, then WF = SAG;
R3: If σ_1 is A_1 and β is B_3, then WF = SAG;
R4: If σ_1 is A_1 and β is B_2, then WF = SWELL;
R5: If σ_1 is A_1 and β is B_1, then WF = SWELL;
R6: If σ_1 is A_1 and β is B_5, then WF = INT;
R7: If σ_1 is A_2 and β is B_4, then WF = TRANSIENT;
R8: If σ_1 is A_2 and β is B_2, then WF = TRANSIENT;
R9: If σ_2 is A_2 and β is B_2, then WF = TRANSIENT;
R10: If σ_1 is A_2 and β is B_1, then WF = SPIKE;
R11: If σ_2 is A_1 and β is B_1, then WF = SPIKE;
R12: If σ_1 is A_1 and β is B_3, then WF = NORMAL;
R13: If σ_1 is A_1 and β is B_1, then WF = NORMAL;
R14: If σ_1 is A_1 and β is B_1, then WF = HARMONIC.

From the above fuzzy rule base, the strength of each rule $\alpha_1, \alpha_2, \ldots, \alpha_{14}$ is evaluated by Zadeh's AND or product rules. In case where there are several rules having the same consequent part, Zadeh's OR rules is used. For example, if a product rule is used for firing strength calculation

$$\text{(For } i\text{th rule)} \quad \alpha_i = \prod_{r=1}^{l} \mu_r^j \tag{15}$$

where μ_r is the membership grade of the rth feature with respect to the jth fuzzy set. Finally, the rules having the same consequent are combined using OR rule to yield the resultant firing

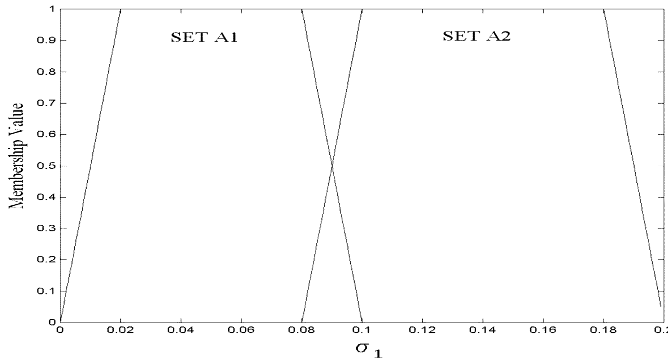

Fig. 11. Membership functions of standard deviation of contour 1 for $b = 5$.

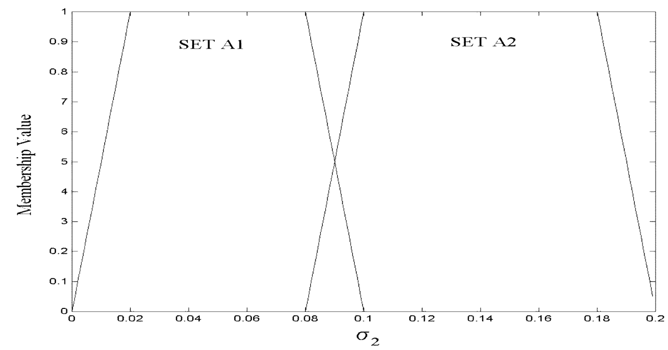

Fig. 12. Membership functions of standard deviation of contour 1 for $b = 1/3$.

strength of the rules as α_N, α_{SA}, α_{SW}, α_{INT}, α_{TR}, α_{SP}, α_{NO}. Here, the suffix N, SA, SW, etc., denote the class of the waveform like normal, sag, swell, etc. The maximum of the above firing strengths is found as

$$\alpha_{\max} = \max(\alpha_N, \alpha_{\mathrm{SA}}, \alpha_{\mathrm{SW}}, \alpha_{\mathrm{INT}}, \alpha_{\mathrm{TR}}, \alpha_{\mathrm{SP}}, \alpha_{\mathrm{NO}}). \tag{16}$$

The value of α in the above string, which becomes $\alpha_{\max,}$ is the waveform class. Although 14 rules were adequate for classifying some of the important power quality violations, many other rules may be required for practical waveforms and waveforms corrupted with large amounts of noise. The duration of the disturbance signal (F_d) can be used to identify whether the disturbance class belongs to instantaneous, momentary, or temporary category. The classification results are presented in Table II for different noise levels in the signal varying from 40 to 20 dB. The total number of simulated events is nearly 800 and the number of events belonging to each class is 100.

As seen from Table II, the classification accuracy for 20-dB noise is found to be lowest and as the noise level reduced to 30 dB, the classification accuracy improves considerably and is 96.5% average.

VI. DISCUSSIONS

From Figs. 1–3, the S-transform contours and associated magnitude versus sampling counts and normalized frequency versus amplitudes clearly reveal the nature of steady state power quality disturbance patterns. This is due to the fact that the S-transform uses the FFT routine to generate the contours of the disturbance signals. Unlike the wavelet transform, these patterns are easier to classify by simply using a couple of features

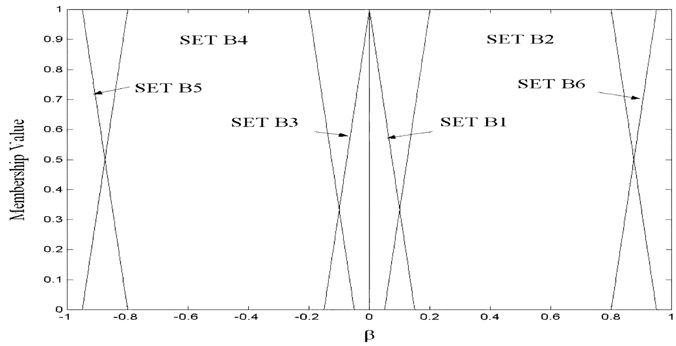

Fig. 13. Membership functions of amplitude factor $\beta(b = 1/3)$.

TABLE II
S-TRANSFORM CLASSIFICATION RESULTS

PQ Disturbance Fuzzy Classification	40dB Noise	30dB Noise	20dB Noise
Voltage Sag	100%	90%	80%
Voltage Swell	100%	100%	60%
Voltage Interruption	100%	100%	100%
Notch	95%	95%	90%
Spike	100%	100%	60%
Transient	100%	100%	50%
Harmonic	100%	90%	85%
Average	99.28%	96.50%	75.00%

like the standard deviation and amplitude factor. Figs. 4–8 show the generalized S-transform contours for PQ violations like transients, notches, and impulses of short durations. These violations are clearly illustrated, as frequency changes in the contour and, thus, localization of these disturbances and optimal features obtained from them have been used with a fuzzy logic-based inferencing scheme to provide accurate classification of the power quality disturbance waveforms. Once the fuzzy recognition system provides the class of the disturbance of a given PQ event, the next step is to obtain the exact time and duration of occurrence along with other detailed informations like the magnitudes, phase angles, frequency, total harmonic distortions if any, etc. The features F_i and F_d provide the instant of occurrence and duration of the power disturbance event, respectively. Other parameters of interest can easily be obtained from the S-transform power disturbance recognition program developed by the authors. Thus, the overall advantage of the S-transform-based fuzzy recognition system over the wavelet one can be summarized as the following.

1) All of the important parameters of a power quality disturbance signal like its amplitude, frequency, total harmonic distortion, phase, time of occurrence, duration, and its class can be obtained from the S-transform output only. For oscillatory transients, both positive and negative peak magnitudes along with peak-to-peak deviations can also be obtained from the S-transform-based power quality assessment software. In case of wavelet transform, a FFT procedure needs to be performed on the signal to obtain several signal parameters in addition to the wavelet coefficients.
2) The classification accuracy of a wavelet-based recognition system may be limited if an important disturbance frequency component has not been precisely extracted by using multiresolution wavelet analysis.
3) The wavelet transform-based recognition system is highly sensitive to the presence of noise, and misclassification occurs beyond a noise level of 1.2% [7], [11] and in case of S-transform, the results are found to be quite satisfactory up to a noise level of nearly 3.5%.

VII. CONCLUSION

This paper has proposed a new approach for detection, localization, and classification of power quality disturbances in a power distribution system. The generalized S-transform with a variable window as a function of PQ signal frequency is used to generate contours and feature vectors for pattern classifications. Unlike the wavelet transform techniques, the new classifier provides a complete characterization of both steady state and transient PQ signals using fuzzy logic-based decision systems. The fuzzy PQ classifier uses 14 rules based on trapezoidal membership functions for most of the PQ disturbance events with an accuracy rate close to 98% average.

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