Measurement and Comparison of Power Quality Disturbances using Discrete Wavelet Transform (DWT) and Discrete Orthogonal S-Transform (DOST)

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Abstract: In the power quality analysis non-stationary nature of voltage distortions require some precise and powerful analytical techniques. The time-frequency representation (TFR) provides a powerful method for identification of the non-stationary of the signals. This paper proposes a comparative study on two techniques for analysis and visualization of voltage distortions with time-varying amplitudes. The techniques include the Discrete Wavelet Transform (DWT) and the Discrete Orthogonal S-Transform (DOST). Several power quality problems are analyzed using both the Discrete Wavelet Transform and DOS–transform, The MATLAB/ SIMULINK based simulation showing clearly the advantage of the DOS– transform in detecting, localizing, and classifying the power quality problems.

Keywords: Power Quality (PQ), Discrete Wavelet Transform, DOS-Transform, Time-Frequency Representation(TFR), Feature extraction, Classification.

1. INTRODUCTION

Power Quality has been a research issue in the power engineering community since the past decade. With extensive use of power electronic devices and microprocessor-based systems requiring high quality of electric power, power quality has become a major concern. Poor electric quality can result in malfunctioning of these devices and may have expensive consequences. To improve the quality of electric power, sources of disturbances must be recognized and controlled [1,8].

This requires continuous monitoring of voltage and current waveforms and their instantaneous sampled values at certain customer sites. But the huge amount of data collected and stored poses a great challenge for data analysis and identification of the type of disturbance. To monitor electrical power quality disturbances, short time discrete Fourier transform (STFT) is most often used [2,3].

But for non- stationary signals, the STFT does not track the signal dynamics properly due to the limitations of a fixed window width chosen a priority [2].On the other hand, Wavelet Transform(WT) [5] uses short windows at high frequencies and long windows at low frequencies; thus closely monitoring the characteristics of non-stationary signals.

These characteristics of the Wavelet Transform [7] provide an automated detection, localization, and classification of power quality disturbance waveforms. Although wavelet multi-resolution analysis (MRA) combined with a large number of neural networks provides efficient classification of power quality (PQ) events, the time-domain featured disturbances [9], such as sags, swells, etc. may not easily be classified. In addition, some of the important disturbance frequency components are not extracted precisely by Discrete Wavelet Transform [4,6].

A more recent time-frequency representation, the S-transform [2,8], has found application in a range of fields. It is similar to a continuous wavelet transform in having progressive resolution but unlike the wavelet transform the S-transform retains absolutely referenced phase information. The S-transform not only estimates the local power spectrum, but also the local phase spectrum. It is also applicable to the general complex valued time series.

One drawback to the S-transform [10] is the size of its redundant representation of the time-frequency plane. It is apparent that a more efficient representation of the S-transform is needed, one that provides a framework on which reduced sampling can be laid. This paper, therefore, presents a new transform, known as Discrete Orthogonal S-Transform (DOST).

II. WAVELET TRANSFORM

The wavelet analysis block transforms the distorted signal into different time-frequency scales. The wavelet transform (WT) uses the wavelet function φ and scaling function ϕ to perform simultaneously the Multi Resolution Analysis (MRA) decomposition and reconstruction of the measured signal. The Wavelet function φ will generate the detailed version (high-frequency components) of the decomposed signal and the scaling function ϕ will generate the approximated version (low-frequency components) of the decomposed signal. The wavelet transform is a well-suited tool for analyzing high-frequency transients in the presence of low-frequency components such as non stationary and non periodic wideband signals [3].

A. *Mathematical Model of DWT*

Before the WT is performed, the wavelet function φ (t)and scaling function ϕ (t) must be defined. The wavelet function serving as a highpass filter can generate the detailed version of the distorted signal, while the scaling function can generate the approximated version of the distorted signal. In general, the discrete φ (t) and ϕ (t) can be defined as follows:

$$\varphi_{j,n}[t] = 2^{j/2}\sum_n d_{j,n}\varphi[2^j t - n] \quad (2)$$

$$\phi_{j,n}[t] = 2^{j/2}\sum_n c_{j,n}\phi[2^j t - n] \quad (3)$$

Where c_j is the scaling coefficient at scale , and d_j is the wavelet coefficient at scale j. Simultaneously, the two functions must be orthogonal and satisfy the properties as follows:

$$\begin{cases} <\phi.\phi> = \dfrac{1}{2^j} \\ <\varphi.\varphi> = \dfrac{1}{2^j} \\ <\phi.\varphi> = 0 \end{cases} \quad (4)$$

Assuming the original signal $x_j[t]$ at scale j is sampled at constant time intervals, thus $x_j[t] = (v_0, v_1 .....v_{N-1})$, the sampling number is $N = 2^J$. is an integer number. For $x_j[t]$, its DWT mathematical recursive equation (as) is presented as follows:

$$DWT(x_j[t]) = \sum_k x_j[t]\phi_{j,k}[t] = 2^{(j+1)/2}(\sum_n u_{j+1,n}\phi[2^{j+1}t - n] + \sum_n w_{j+1,n}\phi[2^{j+1}t - n]) \quad (5)$$

$$0 \le n \le N/2^J - 1$$

Where

$$u_{j+1,n} = \sum_k c_{j,k} v_{j,k} + 2n, 0 \le k \le \frac{N}{2^J} - 1 \quad (6)$$

$$w_{j+1,n} = \sum_k d_{j,k} v_{j,k} + 2n, 0 \le k \le \frac{N}{2^J} - 1 \quad (7)$$

$$d_k = (-1)^k c_{2p-1-k}, p = \frac{N}{2^j} \quad (8)$$

Where $u_{j+1,n}$ is the approximated version at scale j+1. $w_{j+1,n}$ is the detailed version at scale j+1, and j is the translation coefficient. According to the orthonormal wavelet functions and (5), the signal $x_j[t]$ can be reconstructed from both u_{j+1} and w_{j+1}, coefficients using the inverse discrete wavelet transform (IDWT) [as $V_{j+1} \oplus W_{J+1} = V_J$]. Fig. 1 illustrates the three decomposed/reconstructed levels of the DWT algorithm. At each decomposition level, the length of the decomposed signals (e.g., u1 and w1) is half that of the signals(x0) in the previous stage.

B. *parseval's theorem in DWT application*

In Parseval's theorem, assuming a discrete signal x[n] is the current that flows through the 1- resistance, then the consumptive energy of the resistance is equal to the square sum of the spectrum coefficients of the Fourier transform in the frequency domain

$$\frac{1}{N}\sum_{n=<N>}|x[n]|^2 = \sum_{k=<N>}|a_k|^2 \quad (9)$$

where N is the sampling period, and a_k is the spectrum coefficients of the Fourier transform.

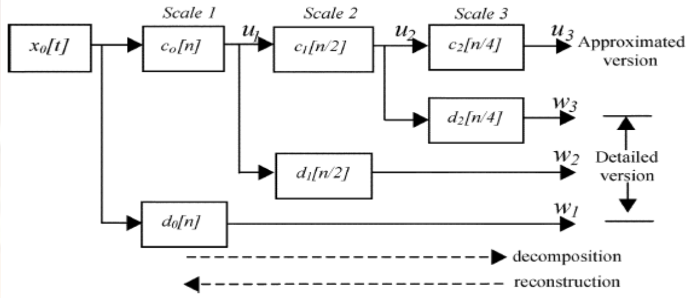


Fig. 1. Three decomposed/reconstructed levels of DWT.

To apply the theorem to the DWT, we use (5) and (9) to obtain (10) that is the Parseval's theorem in the DWT application

$$\frac{1}{N}\sum_t |x[t]|^2 = \frac{1}{N_J}\sum_k |u_{J,k}|^2 + \sum_{j=1}^{J}(\frac{1}{N_j}\sum_k |w_{j,k}|^2) \quad (10)$$

Hence, through the DWT decomposition, the energy of the distorted signal is shown by (10). The first term on the right of (10) denotes the average power of the approximated version of the decomposed signal, while the second term denotes that of the detailed version of the decomposed signal. The second term giving the energy distribution features of the detailed version of distorted signal will be employed to extract the features of power disturbance.

III. S –TRANSFORM AND DOST

A. *S-Transform*

It is well known that information is contained both in the phase and amplitude spectrum. In order to utilize the information contained in phase of the continuous wavelet transform (CWT), it is necessary to modify the phase of the mother wavelet. The CWT *W(τ ,d)* of a function h(t) is defined as

$$W(\tau, d) = \int_{-\infty}^{\infty} h(t) w(t - \tau, d) dt \quad (11)$$

where *w(t,d)*is a scaled replica of the fundamental mother wavelet; the dilation determines the width of the wavelet and this controls the resolution. The S–transform [7,8,9] is obtained by multiplying the CWT with a phase factor, as defined below

$$S(\tau, f)=e^{j2\pi f\tau}W(\tau,d) \quad (12)$$

where the mother wavelet for this particular case is defined as

$$w(t, f)=\frac{|f|}{\sqrt{2\pi}}e^{\frac{t^2f^2}{2}}e^{-i2\pi ft} \quad (13)$$

In equation (2) dilation factor *d* is inverse of frequency *f*. Thus, final form of the continuous S–transform is obtained as

$$S(\tau, f)=\frac{|f|}{\sqrt{2\pi}}\int_{-\infty}^{\infty}h(t)e^{\frac{(t-\tau)^2f^2}{2}}e^{-i2\pi ft}dt \quad (14)$$

and width of the Gaussian window is

$$\sigma(f)=T=1/|f| \quad (15)$$

B. *Discrete Orthogonal S transform:*

There are several reasons to desire an orthogonal time-frequency version of the S-transform. An orthogonal transformation takes an N-point time series to an N-point time-frequency representation, thus achieving the maximum efficiency of representation. Also, each point of the result is linearly independent from any other point.

The transformation matrix (taking the time series to the DOST representation) is orthogonal, meaning that the inverse matrix is equal to the complex conjugate transpose. By being an orthogonal transformation, the vector norm is preserved. Thus a Parseval theorem applies, stating that the norm of the time series equals the norm of the DOST. An orthogonal transform is referred to as an energy preserving transform.

The efficient representation of the S-transform can be defined as the inner products between a time series h[kT] and the basis functions defined as a function of [kT], with the parameters ν (a frequency variable indicative of the centre of a frequency band and analogous to the “voice” of the wavelet transform), β (indicating the width of the frequency band), and τ (a time variable indicating the time localization).

$$S\{h[kT]\}=S\left(\tau T,\frac{\nu}{NT}\right)=\sum_{k=0}^{N-1}h[kT]S_{[\nu,\beta,\tau]}[kT] \quad (16)$$

These basis functions $S_{[\nu,\beta,\tau]}[kT]$ for the general case are defined as

$$S_{[\nu,\beta,\tau]}[kT]=\frac{ie^{-i\pi\tau}}{\sqrt{\beta}}\frac{\left\{e^{-i2\pi(k/N-\tau/\beta)(\nu-\beta/2-1/2)}-e^{-i2\pi(k/N-\tau/\beta)(\nu+\beta/2-1/2)}\right\}}{2\sin[\pi(k/N-\tau/\beta)]} \quad (17)$$

At this point, the sampling of the time-frequency space has not yet been determined. Rules must be applied to the sampling of the time-frequency space to ensure orthogonality. These rules are as follows

- Rule 1. τ = 0, 1, . . . , β −1.
- Rule 2. ν and β must be selected such that each Fourier frequency sample is used once and only once.

Implicit in this definition is the phase correction of the S-transform that distinguishes it from the wavelet or filter bank approach. Here the parameters ν, β, τ are integers defined such that the functions do form a basis. For each voice, there are one or more local time samples (τ), this number being equal to β (see Rule 1) thus the wider the frequency resolution (large β), the more samples in time (large τ). This can be seen as a consequence of the uncertainty principle.

Examples and methods for determining these parameters are described below. Distinct from a wavelet function, these basis functions have no vanishing moments (in fact the functions are normalized to unit area). These basis functions are not translations of a single function, and they are not self-similar.

IV. SIMULATION MODEL AND RESULTS

A. *Power Disturbance Data Set*

The DWT and DOST presented in this work is designed to recognize pure sine wave(a) and four types of power quality disturbances including voltage sag(b), voltage swell(c), interruption(d) and oscillatory transient(e), based on the test system shown in Fig. 2 and generated waveforms using MATLAB/SIMULINK are shown in Fig. 3.

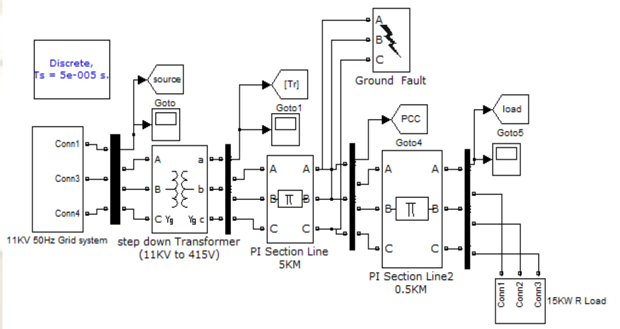
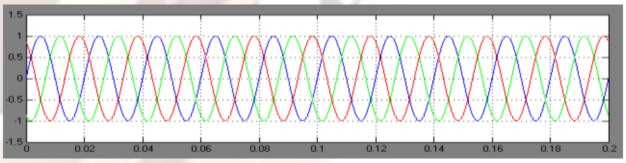
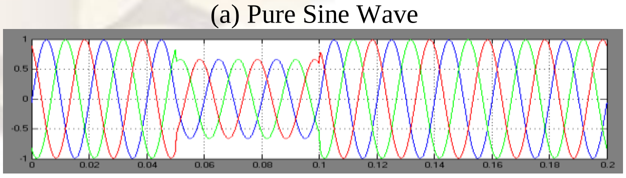


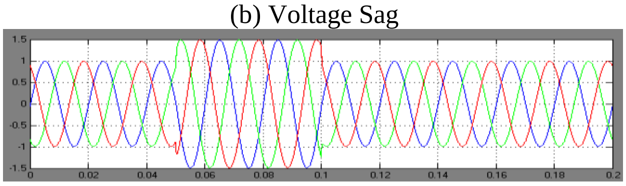
Fig. 2 PQ Disturbances generating test system



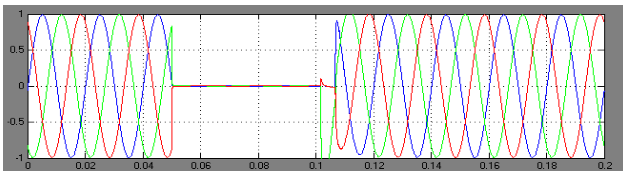
(a) Pure Sine Wave



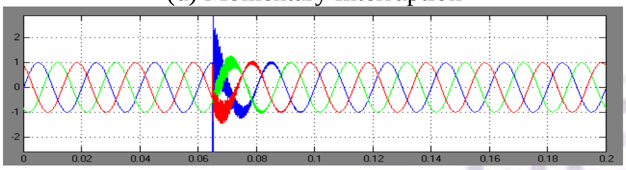
(b) Voltage Sag



(c) Voltage Swell



(d) Momentary Interruption



(e) Impulsive Transient

Fig. 3 Typical power quality disturbance categories

B. WT-Simulation Results

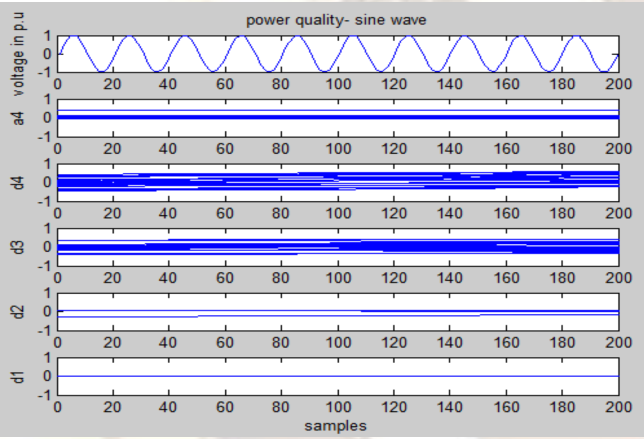


Fig. 4 WT-Contour for sinusoid voltage

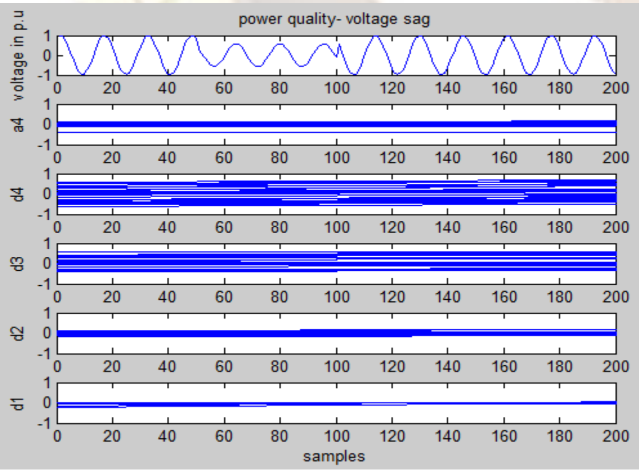


Fig. 5 WT-Contour for voltage sag

Fig.4-8 shows the output of Wavelet Transform.This thesis has been employed to a few types of disturbances and can be applied for other types of disturbances such as notches, glitches, harmonics etc.

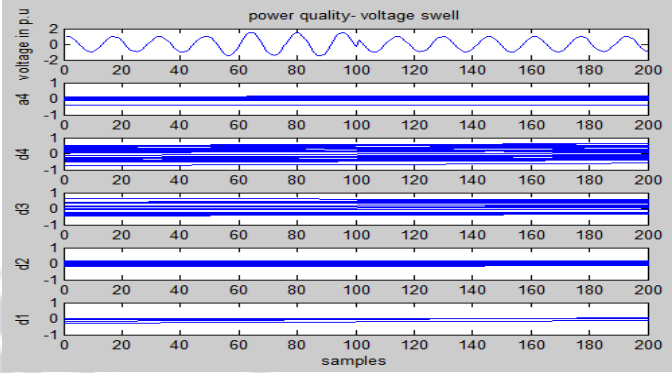


Fig. 6 WT-Contour for voltage swell

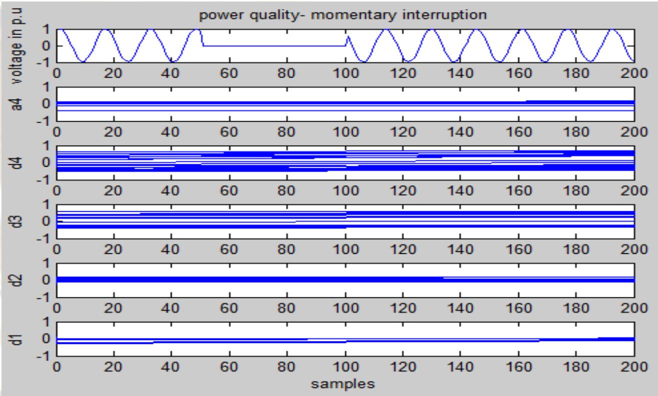


Fig. 7 WT-Contour for momentary interruption

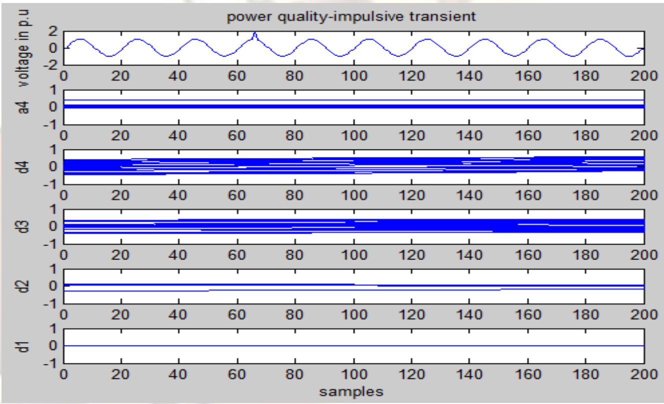


Fig. 8 WT-Contour for impulsive transient

C. DOST-Simulation results(2D & 3D)

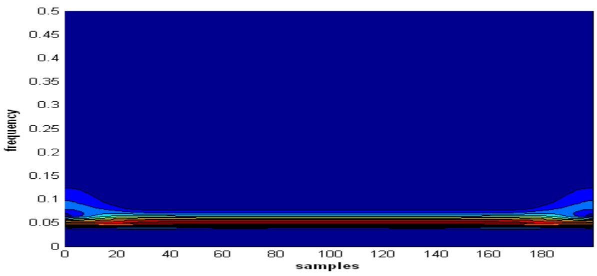


Fig. 9 DOST-Contour (2D) for sinusoid voltage

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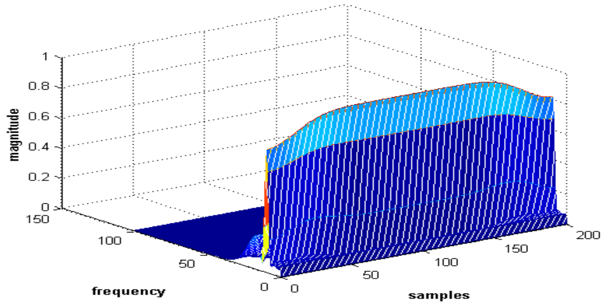

Fig. 10 DOST-Contour (3D) for sinusoid voltage

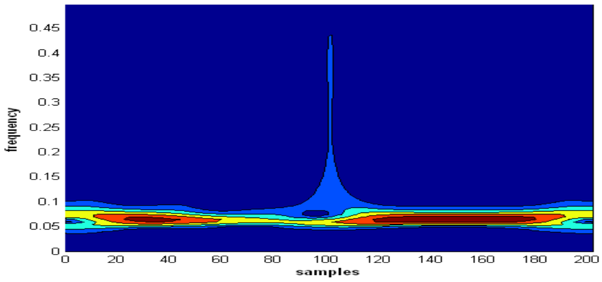

Fig. 11 DOST-Contour (2D) for voltage sag

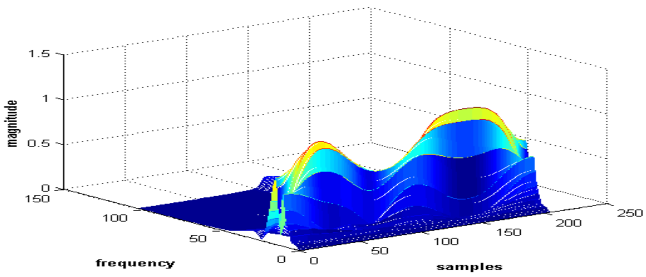

Fig. 12 DOST-Contour (3D) for voltage sag

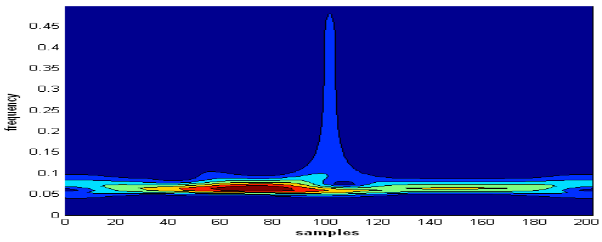

Fig. 13 DOST-Contour (2D) for voltage swell

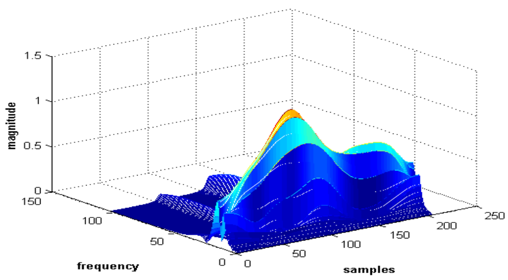

Fig. 14 DOST-Contour (3D) for voltage swell

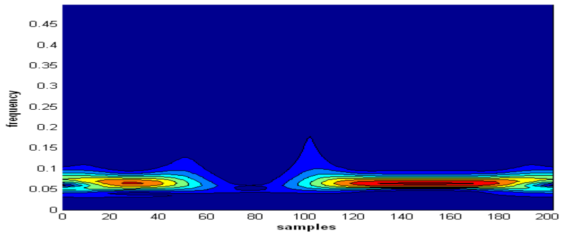

Fig. 15 DOST-Contour (2D) for momentary interruption

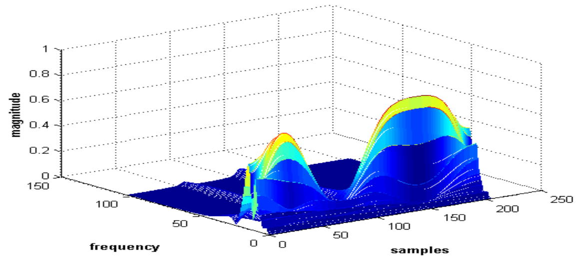

Fig. 16 DOST-Contour (3D) for momentary interruption

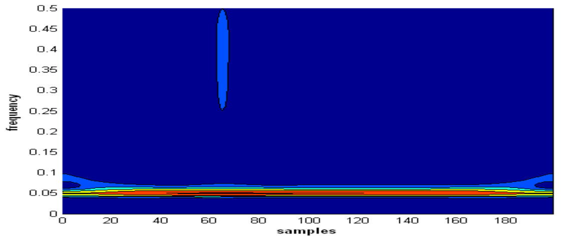

Fig. 17 DOST-Contour (2D) for oscillatory transient

Figure 9-18, show the 2-D, 3-D mesh plot for various signals. Power quality disturbance signals such as swell, sag, oscillatory transients, momentary interruption etc. must be detected and classified properly to initiate corrective measures to ensure quality of power. S-Transform generates contours, which are suitable for classification by simple visual inspection unlike wavelet transforms (WT) that requires specific methods like Standard-Multi resolution analysis (MRA) for classification.

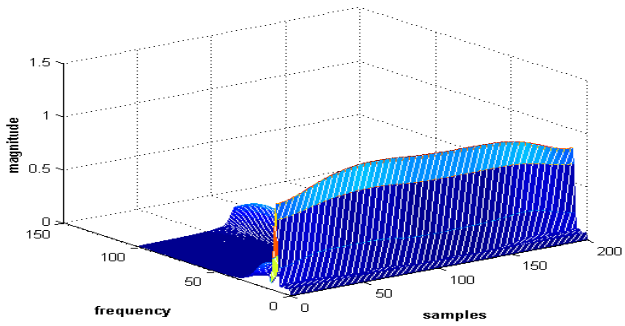

Fig. 18 DOST-Contour (3D) for oscillatory transient

Fig.4-8, shows the detailed version of Fig. 3a, 3b, 3c, 3d, 3e after application of db4 wavelet in four level of decomposition. Although, detailed version indicates presence of harmonics at different times, but can't be classified. From the S-Transform plot, magnitude, frequency and time information can be readily obtained to detect, localize and visually classify signal events in three-dimensional space.

V. CONCLUSION

The simulation results showed that the proposed method has the ability of recognizing and classifying different power disturbance types efficiently compared with Discrete Wavelet Transform (DWT). Discrete Orthogonal S Transform (DOST) generates contours, which are suitable for classification by simple visual inspection unlike DWT that requires specific methods like Multi Resolution Analysis (MRA), Support Vector Machine (SVM) and Probabilistic Neural Network (PNN) for classification. The DOS-Transform, seems to be a powerful tool for detection, localization and classification of power system disturbances compared to Short Time Fourier Transform (STFT), Fast Fourier Transform (FFT) Discrete Fourier Transform (FFT) as well as Discrete Wavelet Transforms (DWT).

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