Medwell PUBLISHING

International Journal of Electrical and Power Engineering 3 (1): 59-68, 2009
ISSN: 1990-7958

A Novel Method of Power Quality Disturbances Measures Using Discrete Orthogonal S Transform (DOST) with Wavelet Support Vector Machine (WSVM) Classifier

[1]A. Vetrivel, [2]N. Malmurugan and [3]Jovitha Jerome
[1]Department of Electrical and Electronics Engineering,
Institute of Road and Transport Technology, Erode-638316, India
[2]Satyam Computer Services Limited, #05-2A, Ultro Building, 486058, Singapore
[3]Department of Electrical and Electronics Engineering,
PSG College of Technology, Coimbatore-641004, India

Abstract: This study proposes a novel method based on Discrete Orthogonal S-Transform (DOST) and Wavelet Support Vector Machines (WSVM) for detection and classification of power quality disturbances. DOS-transform is mainly used to extract features of power quality disturbances and support vector machines are mainly used to construct a multi-class classifier, which can classify power quality disturbances according to the extracted features. Results of simulation and analysis demonstrate that the proposed method can achieve higher correct identification rate, better convergence property and less training time compared with the method based on Probabilistic Neural Network (PNN). Therefore, through this method power quality disturbances can be detected and classified effectively, accurately and reliably.

Key words: Power Quality (PQ), DOS-transform, wavelet transform, feature extraction, classification, WSVM

INTRODUCTION

With the ever-growing demand of electricity in the modern civilized society, the total generation of electricity has also increased remarkably in the last few decades. But the quality of electricity has deteriorated to such an extent that it has become an increasing concern for electric utilities and their customers. The term power quality is generally used to express the variation of voltage, current or frequency with respect to steady state sinusoidal waveform at a nominal system frequency (Arrillaga *et al*., 2000; Bollen, 2000). Thus, power quality is intricately related to power system disturbances. Such disturbances are created mostly due to extensive use of power electronic devices and non-linear loads in electrical power system and consequently the sensitive detection and accurate classification of power disturbances have become very much necessary to ensure power quality (Vetrivel *et al*., 2007). STFT (Santoso *et al*., 1996) cannot be used successfully to analyze transient signals comprising both high and low frequency components. Although, wavelet (Santoso *et al*., 1997) 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, such as sags, swells, etc. may not easily be classified. In addition, frequency components of some of the important disturbance are not extracted precisely by wavelet transform (Gouda *et al*., 1999).

A more recent time-frequency representation, the S-transform (Stockwell *et al*., 1996, 1997a; Reddy *et al*., 2004), is similar to a continuous wavelet transform in having progressive resolution but unlike the wavelet transform the S-transform retains absolutely referenced phase information. Absolutely referenced phase information is the phase information given by the S-transform refers to the argument of the sinusoid at zero time (which is the same meaning of phase given by the fourier transform). The S-transform not only estimates the local power spectrum, but also the local phase spectrum. One drawback to the S-transform 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 study, therefore, presents a new transform, known as Discrete Orthogonal S-transform (DOST) (Stockwell, 2007). Recently, ST and DOST are being used in Power quality analysis DOST is mainly used to extract features of PQ disturbances and WSVMs are mainly used to construct a multi-class classifier to classify PQ disturbances according to the extracted features.

Corresponding Author: N. Malmurugan, Satyam Computer Services Limited, #05-2A, Ultro Building, 486058, Singapore

S-TRANSFORM, DOST AND WSVM

S-transform: The CWT W(τ, d) of a function h (t) is defined as:

$$W(\tau, d) = \int_{-\infty}^{\infty} h(t) w(t-\tau, d) dt \quad (1)$$

where, w (τ, 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 (Stockwell *et al.*, 1996, 1997a) is obtained by multiplying the CWT with a phase factor, as defined:

$$S(\tau, f) = e^{j2\pi f\tau} W(\tau, d) \quad (2)$$

where, the mother wavelet for this particular case is defined as:

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{\frac{t^2 f^2}{2}} e^{-i2\pi ft} \quad (3)$$

In Eq. (2) dilation factor d is inverse of frequency f. Thus, final form of the continuous S-transform is obtained as:

$$S(\tau, f) = \frac{|f|}{\sqrt{2\pi}} \int_{-\infty}^{\infty} h(t)\, e^{\frac{(t-\tau)^2 f^2}{2}} e^{-i2\pi ft} dt \quad (4)$$

and width of the Gaussian window is

$$\sigma(f) = T = 1/|f| \quad (5)$$

Since, S-transform is a representation of local spectra, Fourier or time average spectrum can be directly obtained by averaging local spectra through inverse S transform, as given by Eq. (6):

$$h(t) = \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} S(\tau, f) d\tau \right\} e^{j2\pi ft} df \quad (6)$$

The discrete S-transform is defined as follows. Let, h (kT), k = 0,1, ……., N-1 denote a discrete time series corresponding to h (t) with a time sampling interval of T. The discrete Fourier transform of h (kT) is obtained as:

$$H\left[\frac{n}{NT}\right] = \frac{1}{N} \sum_{k=0}^{N-1} h[kT] e^{\frac{-j2\pi nk}{N}} \quad (7)$$

where, n = 0, 1, ………, N-1. In the discrete case the S-transform (Stockwell *et al.*, 1996, 1997a), is the projection of the vector defined by time series h (kT) onto a spanning set of vectors. Spanning vectors are not orthogonal and elements of S-transform are not independent. Each basis vector is divided into N localized vectors by an element by-element product with N shifted Gaussian windows. Using Eq. (4), S-transform of a discrete time series h (kT) is obtained by letting f tending to n/(NT) and t tending to jT. Thus, discrete S-transform is given by Eq. (8):

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] G(m,n) e^{\frac{i2\pi nj}{N}} \quad (8)$$

where,

$$G(m,n) = e^{\frac{-2\pi^2 m^2}{n^2}} \quad (9)$$

and α = 1/b; n ≠ 0; n = 1,2,3,4 ….. N-1; j = m = 0,1,2,3,4 …….., N-1; N = total number of samples. A typical value of b has been taken in the range of 0.333-5 for different resolutions. For low frequencies, a high value of b is chosen and for high frequencies, lower value of b is chosen to provide suitable frequency resolutions. For n = 0, the S-transform assumes the form represented by Eq. (10).

$$S(jT, 0) = \frac{1}{N} \sum_{m=0}^{N-1} h\left[\frac{m}{NT}\right] \quad (10)$$

The amplitude of S-matrix is obtained from |S(jT, n/(NT))|. Equation 10 averages zero frequency components. The average of amplitude of S-matrix over time results in Fourier spectrum.

Discrete orthogonal s-transform: There are several reasons to desire an orthonormal time-frequency version of the S-transform (Stockwell, 2007). As 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. 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 center 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).

$$S\{h[kT]\} = S\left(\tau T, \frac{\nu}{NT}\right) = \sum_{k=0}^{N-1} h[kT] S_{[\nu,\beta,\tau]}[kT] \quad (11)$$

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

$$S_{[\nu,\beta,\tau]}[kT] = \frac{ie^{-i\pi\tau}}{\sqrt{\beta}} \frac{\left\{ e^{-i2\pi(k/N-\tau/\beta)(\nu-\beta/2-1/2)} - e^{-i2\pi(k/N-\tau/\beta)(\nu+\beta/2-1/2)} \right\}}{2\sin\left[\pi(k/N-\tau/\beta)\right]} \tag{12}$$

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, $\tau = 0, 1, \ldots, \beta - 1$.
- 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 (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. Distinct from a wavelet function, these basis functions have no vanishing moments. These basis functions are not translations of a single function and they are not self-similar.

Orthonormal basis functions with octave sampling: In order to compare, the DOST with orthonormal wavelet transforms and with the S-transform, an octave sampling of the time-frequency domain is illustrated. This has the property of progressive resolution that both the S-transform and wavelet transforms share. Octave sampling implies that the voice bandwidth doubles for each increasing voice (as sampling allows).

By imposing specific rules on the basis functions (here octave sampling) it implies a strict definition for ν and β. By introducing a new variable p, which corresponds to the octave number $p = 0, 1, 2, \ldots, \log2(N) - 1$ one can define all the parameters (ν, β, τ) of Eq. 12 in terms of p as follows:

For $p > 1$, we have:

$$p = 2, \ldots, \log2(N)-1, \tag{13}$$

$$\nu = 2(p-1) + 2(p-2), \tag{14}$$

$$\beta = 2(p-1), \tag{15}$$

$$\tau = 0, 1, \ldots, 2(p-1)-1. \tag{16}$$

For the case $p = 0$, then $\nu = 0$, $\beta = 1$ and $\tau = 0$. Also when $p = 1$, then $\nu = 1$, $\beta = 1$ and $\tau = 0$. Thus, the DOST basis functions for octave sampling of a time series is given as follows (by application of Eq. (13-16) into Eq. (12)):

$$S_{[p,\tau]}[kT] = \frac{ie^{-i\pi\tau}}{\sqrt{2^{(p-1)/2}}} \frac{\left\{ \begin{matrix} e^{-i2\pi\left(k/N-\tau/2^{p-1}\right)\left(2^{p-1}--1/2\right)} \\ -e^{-i2\pi\left(k/N-\tau/2^{p-1}\right)\left(2^{p}-1/2\right)} \end{matrix} \right\}}{2\sin\left[\pi\left(k/N-\tau/2^{p-1}\right)\right]} \tag{17}$$

Derivation of the basis functions: By extending filter bank theory, in combination with the unique phase correction of the S-transform, the time domain basis functions for the S-transform are developed. The novel idea is to create a new orthonormal basis for a time-frequency representation by taking linear combinations of the original Fourier basis functions in band limited subspaces. Within a frequency band (i.e., a particular voice), several orthogonal basis functions are formed by a linear combination of the Fourier basis functions in that frequency band. There are β components in this operation. Thus, β basis functions can be derived by applying the appropriate phase functions to the components (where each of the β basis functions is indexed by $\tau = 0, 1, \ldots, \beta-1$). The key to creating orthogonal functions is the careful selection of the frequency shift applied to the Fourier basis functions. This action is the analog of the phase correction of the S-transform. This is where the absolutely referenced phase information originates and it is what distinguishes these basis functions from wavelets (i.e., they are not self-similar). The basis functions can be derived by starting with a partitioning of the spectrum (a simple restricted sum of complex-valued Fourier basis functions) defined in the time domain (function of (kT)), centered at frequency ν with a bandwidth of β and applying the appropriate phase and frequency shifts:

$$S[kT]_{[\nu,\beta,\tau]} = \frac{1}{\beta} \sum_{f=\nu-\beta/2}^{\nu+\beta/2-1} \exp\left(i2\pi\frac{k}{N}f\right) \exp\left(-i2\pi\frac{\tau}{\beta}f\right) \exp\left(-i2\pi\frac{N}{2NT}\tau T\right) \tag{18}$$

where, $1/\sqrt{\beta}$ is a normalization factor to insure orthonormality of the basis functions.

Thus, the basis function for the discrete orthonormal S-transform (DOST) of voice frequency ν, bandwidth β and time index τ can be written as:

$$S[kT]_{[\nu,\beta,\tau]} = \frac{e^{-i\pi\tau}}{\sqrt{\beta}} \sum_{f=\nu-\beta/2}^{\nu+\beta/2-1} \exp\left(i2\pi\left(\frac{k}{N}-\frac{\tau}{\beta}\right)f\right) \tag{19}$$

Application of the identity

$$c + cx + ... + cx^{n-1} = \frac{c(1-x^n)}{1-x} \quad (20)$$

to Eq. (19) leads to Eq. (12). As can be seen in Eq. (19), the function has no poles (β is always greater than zero). In Eq. (12), there is an apparent pole where the denominator goes to zero (where $k/N \rightarrow \tau/\beta$), but application of LHopitals rule shows that the limit of the basis function as $k/N \rightarrow \tau/\beta$ is well behaved and equal to:

$$\lim_{k/N \rightarrow \tau/\beta} S(kT)_{[\nu,\beta,\tau]} = \sqrt{\beta} e^{i\pi\tau} \quad (21)$$

One advantage of this method is that one can directly calculate any voice, without having to iterate through a series of intermediate steps. Also, there is no filter design involved nor any upsampling or downsampling algorithms required. Another advantage is that it allows one to directly apply the ideas of power spectrum estimation, such as applying windows and apodizing functions, to the analysis of the local spectrum of a time series.

Note that in a departure from filter bank theory, the sum is centered on the voice frequency ν. In other words, a frequency translation has been applied. The operation of calculating the inner product of a time series with this basis function not equivalent to a simple filtering operation (in the asymptotically simple case of the time series consisting of an oscillating sinusoid, the resulting voice will be a constant, in amplitude and phase, for each time sample). This frequency shift is vital when the characteristic of absolutely referenced phase information (and cross local spectrum analysis and generalized instantaneous frequency) is described and is the distinguishing difference between the S-transform approach and the wavelet/filter bank approach. This shift in frequency is the key feature of the original S-transform. In Eq. (17), the n voice S (jT, n/NT) has the same frequency translation applied by the shift of the spectrum H ((m +n)/NT) by n which centers the spectrum around the n frequency.

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{\frac{-2\pi^2 m^2}{n^2}} e^{\frac{i2\pi nj}{N}}, n \neq 0 \quad (22)$$

It is precisely, this property of the basis functions that provides absolutely referenced phase information and it is also this property that implies that the basis functions are not self-similar. It is easy to show that the basis functions are indeed orthonormal and have compact support in frequency. They are not compactly supported in time, but they are local. The property of compact support refers to a particular transform. An orthonormal wavelet does not have compact support under a Fourier transform. By the uncertainty principle, one cannot have a compactly supported function, which has a compact Fourier transform. These basis functions are compact in frequency and also local in time, while maintaining orthogonality. All that is required is that the ν and β values are chosen such that the bandwidths do not overlap and that all discrete frequencies are sampled. The utility of these basis functions is that they create a road map for one to overlap bandwidths and oversample in time in an arbitrary (perhaps data adaptive) manner to achieve any desired sampling of the time-frequency space.

The DOST has the following properties: Exact analytical definition of a basis for the S-transform.

- An orthogonal time-frequency transform from, which the discrete Fourier transform can be derived as a special case.
- An orthogonal time-frequency representation that collapses over the time variable to exactly give the discrete Fourier transform spectrum.
- Absolutely referenced phase, thus giving meaning to the phase of an orthonormal time-frequency representation.
- The ability to directly compare the phase of two time series in a localized cross spectral analysis.
- The ability to employ a channel instantaneous frequency to each signal of the DOST.
- A general definition of a time-frequency representation to which one can apply any of the standard windows of power spectrum analysis in order to perform a localized power spectrum analysis.
- The DOST can be extended in a straightforward method to higher dimensions for applications such as image processing and volumetric data analysis, as has been done with the S-transform.

Wavelet support vector machine classifier: SVM has become a hot research topic in the international machine learning field because of its excellent statistical learning performance and superior classification performance (Burges, 1998; Lin and Hsu, 2002; Mitra *et al.*, 2002). Simply, SVM can be comprehended as follows: it divides two specified training samples, which belong to two different categories through constructing an Optimal Separating Hyperplane (OSH) either in the original space or in the mapped higher dimensional space. The principle of constructing OSH is to guarantee that the distance between each training sample and OSH should be maximum.

If data are linearly separable in the input space, a binary classification task is taken into account. Let $\{(x_i,y_i)\}$ $(1 \le i \le N)$ be a linearly separable set. Where, $x_i \varepsilon R^d$, $y_i \varepsilon \{-1, 1\}$ and y_i are labels of categories. The general expression of the linear discrimination function in d-dimension space is defined as g (x) = w.x + b and the corresponding equation of OSH is as follows: w.x+b = 0. Normalize g (x) and make all the x_i meet |g(x)| = 1, that is, the samples, which are the closest to OSH meet |g(x)| = 1. Hence, the separating interval is equal to 2/|w| and solving OSH is equivalent to minimizin g|w|. The object function is as follows:

$$\min \phi(w)=\frac{1}{2}\|w\|^2 \quad (23)$$

Subject to the constraints:

$$y_i\,(w.x_i + b)\ge 1,\ i = 1, \ldots, N \quad (24)$$

When adopting Lagrangian algorithm and introducing Lagrangian multipliers $\alpha = \{\alpha_1, \ldots, \alpha_N\}$, the problem mentioned above can be converted into a quadratic programming problem and OSH can also be solved. Where:

$$w = \sum_i \alpha_i y_i x_i\ ,\ x_i$$

are the samples only appearing in the separating interval planes. These samples are named as support vectors and the classification function is defined as follows:

$$f(x)=\text{sgn}\left(\sum_i \alpha_i y_i x_i\,.x+b\right) \quad (25)$$

If data are not linearly separable in the input space, the object function is turned into as follows:

$$\min \phi(w,\xi)=\frac{1}{2}\|w\|^2+C\left(\sum_{i=1}^{N}\xi_i\right) \quad (26)$$

where,

ξ = Slack variable.

C = Penalty factor.

Simultaneously, through a non-linear transform $\phi(.)$ the input space is mapped into a higher dimensional space named feature space in which OSH can be solved. Additionally, the inner product calculation is turned into K (x_i, x_j) = Φ (x_i).Φ (x_j); where, K (x_i, x_j) named kernel function is defined as inner product in Hilbert space. Thus, the final decision function for classification can be represented as follows:

$$f(x)=\text{sgn}\left(\sum_i \alpha_i y_i K(x,x_i).x+b\right) \quad (27)$$

Wavelet kernels with SVMs will construct WSVMs (Zhang *et al*., 2004). The existence of wavelet kernels is proven by results of theoretic analysis. Our wavelet kernel is a kind of multidimensional wavelet function that can approximate arbitrary functions. It is not surprising that wavelet kernel gives better approximation than Gaussian kernel, Notice that the wavelet kernel is orthonormal (or orthonormal approximately), whereas the Gaussian kernel is not. In other words, the Gaussian kernel is correlative or even redundancy, which is the possible reason why the training speed of the wavelet kernel SVM is slightly faster than the Gaussian kernel SVM. We construct a translation-invariant wavelet kernel by a wavelet function adopted in

$$h(x)=\cos(1.75x)\exp(-\frac{x^2}{2}) \quad (28)$$

Given the mother wavelet (28) and the dilation a, a, x ε R. If x, x_i ε R^N, the wavelet kernel of this mother wavelet is

$$\begin{aligned}K(x,x_i)&=\prod_{j=1}^{N}h\left(\frac{x^j-x_i^j}{a_i}\right)\\&=\prod_{j=1}^{N}\left(\cos\left(1.75x\frac{(x^j-x_i^j)}{a_i}\right)\exp\left(-\frac{\|x^j-x_i^j\|^2}{2a_i^{\,2}}\right)\right)\end{aligned} \quad (29)$$

which is an admissible SV kernel, where the, x_i^j denotes the jth component of the ith training example.

PROPOSED ALGORITHM FOR POWER QUALITY ANALYSIS USING DOST WITH WSVM

The proposed method of DOST with WSVM classifier is illustrated in Fig. 1. There are mainly two tasks for detection and classification of PQ disturbances, one is extracting features and the other is recognition and classification. DOST has excellent time-frequency analysis performance suitable for analyzing non-stationary signals and SVM exhibits excellent statistical learning ability suitable for recognition and classification. Therefore, this paper proposes a novel method based on DOST and WSVMs for detection and classification of PQ disturbances. DOST is mainly used to extract features of PQ disturbances and WSVMs are mainly used to construct a multi-class classifier to classify PQ disturbances according to the extracted features.

Pre-processing: The pre-processing stage involves two steps. In the 1st step, the captured signal is processed with the signal processing technique i.e., DOS-transform. This way time domain signal is converted into a time-frequency contour and the DOS-transform matrix so obtained contains the useful features of the disturbance signal. In the 2nd step, the useful features are extracted from the DOS-transform matrix. The features are as standard deviation of the highest DOS-transform contour, the energy of the highest DOS-transform contour, variance of the highest DOS-transform contour, difference between the highest and lowest value of the DOS-transform contour with a Gaussian window of spread 1.

Multi-class WSVM classification tree: An original SVM can be implemented mainly by two algorithms: 1-to-multi algorithm and 1-to-1 algorithm. The 1-to-multi algorithm solves an N-class problem through N binary classifiers. The ith SVM takes samples of the ith class as the positive training samples and the rest samples as the negative samples. The disadvantages of the 1-to multi algorithm are as follow: the number of training samples is large, training is difficult and the generalization error is unbounded. The 1-to-1 algorithm constructs all the possible binary classifiers with N-class training samples and each classifier is only trained by the binary-class training samples of the N classes, which results in constructing N(N-1)/2 classifiers. It is determined by the voting method that which class the specified sample belongs to. The disadvantages of the 1-to-1 algorithm are as follow: the generalization error is unbounded and the number of classifiers rapidly increases with the number of classes. Additionally, the classification dead zone problem perhaps exists in the previous two algorithms.

In order to overcome the disadvantages of the two algorithms mentioned above, the thought of cluster analysis is drawn from pattern recognition and the multi-class SVM classification tree is constructed through the grade-cluster method to classify PQ disturbances. The basic thought is as follows: firstly the PQ disturbance set needing to be classified is divided into two subsets according to the similarity of the chosen feature vectors and then the two subsets are divided into two subsets separately again according to the same principle. The division will continue until the classification task is finished. The multi-class SVM classification tree of PQ disturbances is shown in Fig. 2. It can be seen that there

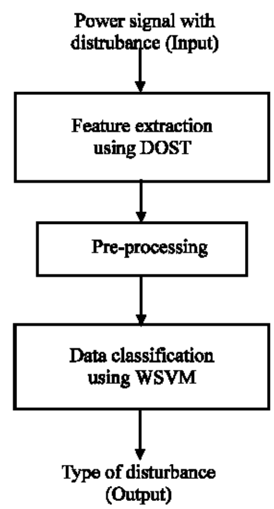

Fig. 1: Feature extraction and classification process

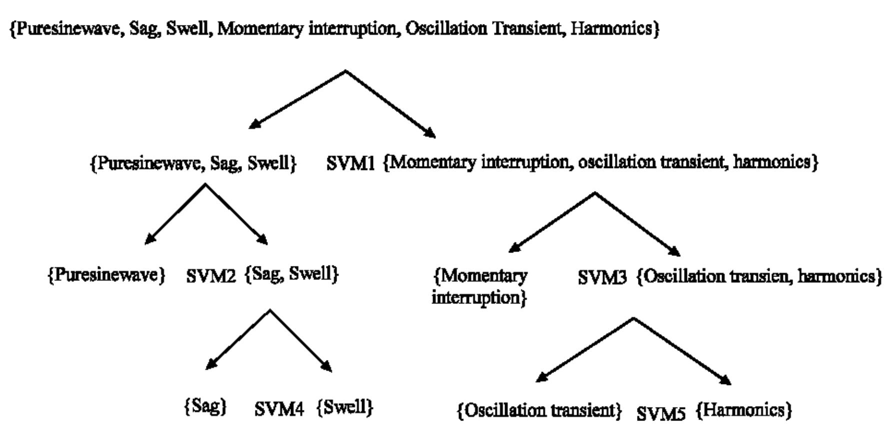

Fig. 2: Multi-class WSVM classification tree

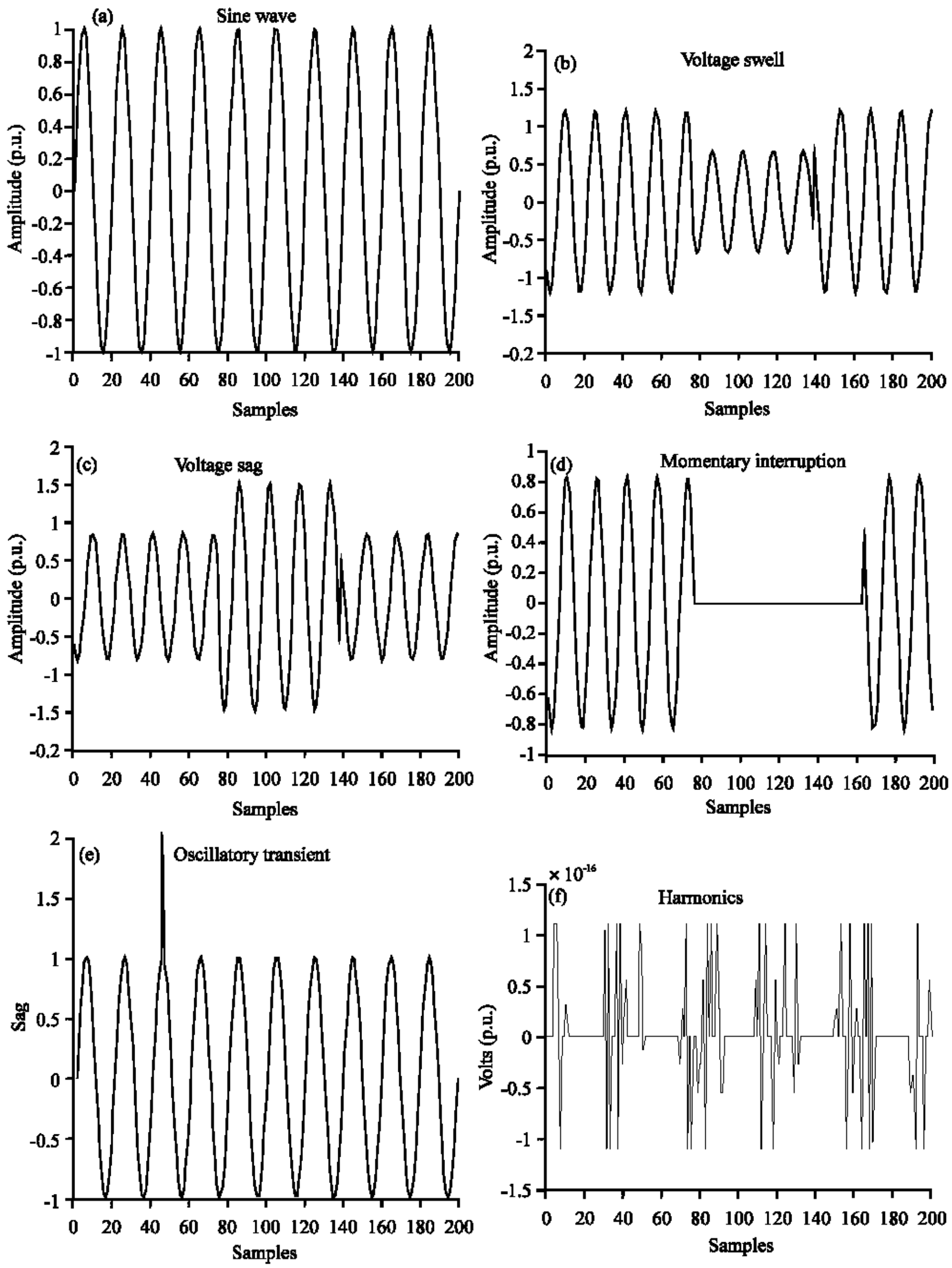

Fig. 3: Typical power quality disturbance categories

are 4 SVMs in the multi-class SVM application tree and each SVM chooses different feature vector to implement binary classification. WSVM has less training time and less testing time than ANN.

Power disturbance data set: The entire research presented in this study is tested with standard Power Disturbance set given in the Fig. 3 to recognize type A of pure sinewave and four types of power quality disturbances including type B voltage sag, type C voltage swell, type D interruption, type E oscillatory transient and type F harmonics. Frequency (f) is normalized with respect to a base frequency.

RESULTS AND DISCUSSION

The power system 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. The

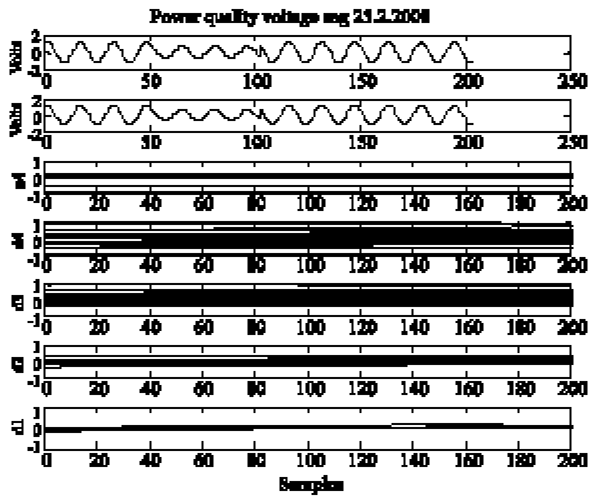

Fig. 4: Details for db4 wavelet for voltage sag

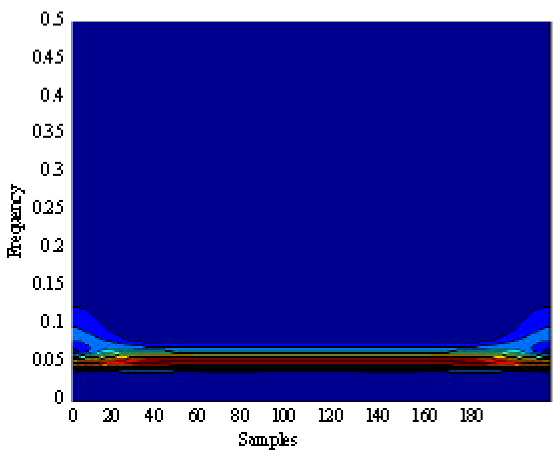

Fig. 5: DOST-contour for sinusoidal voltage

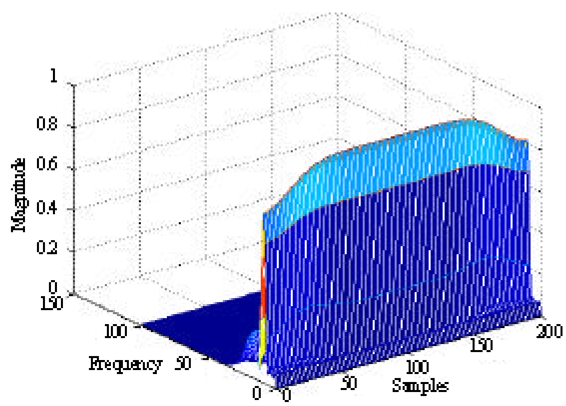

Fig. 6: DOST-contour (3-D) for sinusoidal voltage

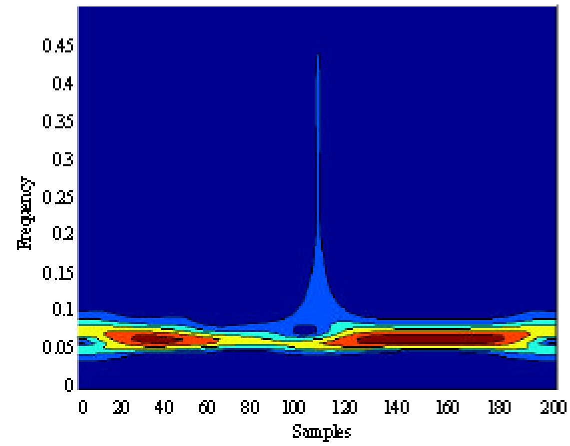

Fig. 7: DOST-contour for voltage sag

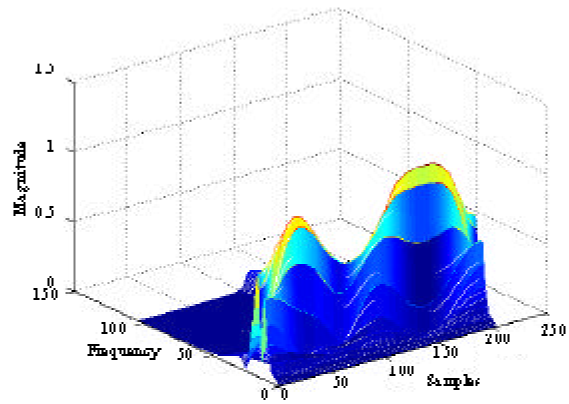

Fig. 8: DOST-contour (3-D) for voltage sag

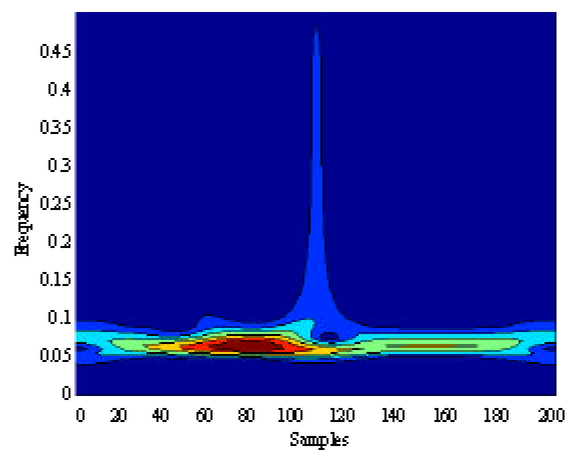

Fig. 9: DOST-contour for voltage swell

modified discrete wavelet transform, termed as DOS-transform, seems to be a powerful tool for detection, localization and classification of power system disturbances compared to Short Time Fourier Transform (STFT) as well as Wavelet Transforms (WT). DOS-transform generates contours, which are suitable for

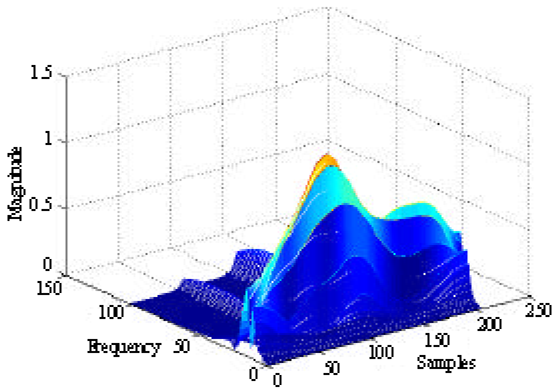

Fig. 10: DOST-contour (3-D) for voltage swell

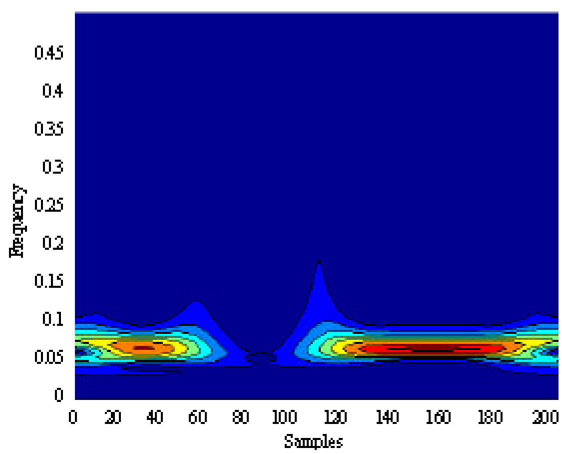

Fig. 11: DOST-contour for momentary interruption

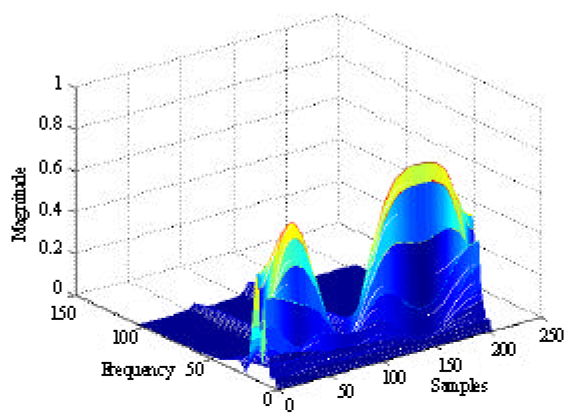

Fig. 12: DOST-contour (3-D) for momentary interruption

classification by simple visual inspection unlike wavelet transforms (WT). DOS-transform generates contours which are suitable for classification by simple visual inspection unlike wavelet transform that requires specific

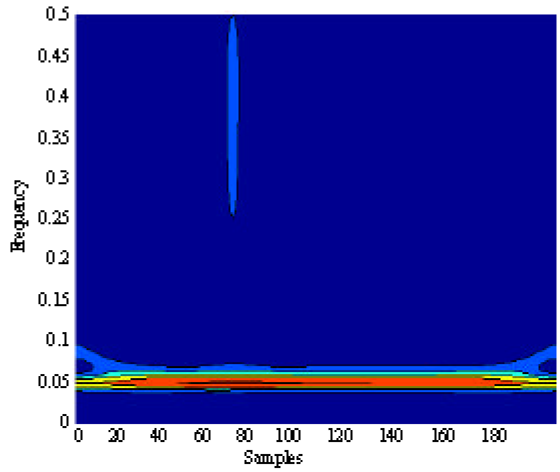

Fig. 13: DOST-contour for impulse transient

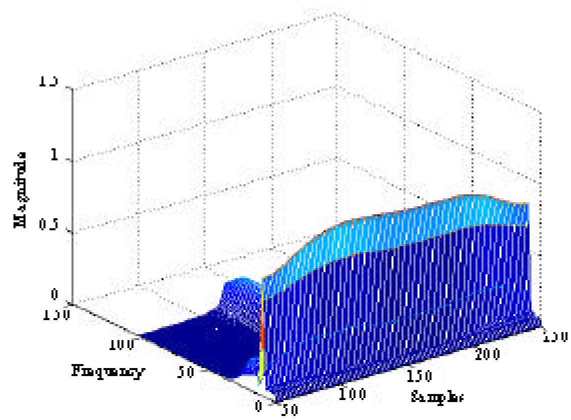

Fig. 14: DOST-contour (3-D) for impulse transient

methods like Standard-Multi resolution analysis (Std_MRA) for classification. DOS-transform has been employed to a few types of disturbances in this article and can be applied for other types of disturbances such as notches, glitches etc.

Figure 4 shows the detailed version of Fig. 3 c 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. Figure 5-14, show the 2-D, 3-D mesh plot for various signals. From the plot, magnitude, frequency and time information can be readily obtained to detect, localize and visually classify signal events in three-dimensional space.

The excellent statistical learning ability of WSVM compared with ANN, WSVM exhibits more excellent performances such as no local optimum problem, no over-fit or under-fit problem, better convergence property, less training samples, higher correct identification rate and higher reliability. In addition, comparison of classification

Table 1: Comparison of classification results

Type	No of data sets	Proposed method Correctly	Incorrect	Accuracy rate (%)	Wavelet transform-based PNN Correctly	Incorrect	Accuracy rate (%)	Wavelet with SVM Correctly	Incorrect	Accuracy rate (%)
Pure sine wave	100	100	-	100	100	-	100	100	-	100
Sag	100	96	4	96	92	8	92	94	6	94
Swell	100	94	6	94	92	8	92	93	7	93
Momentary interruption	100	94	6	94	92	8	92	93	7	93
Oscillatory transient	100	94	6	94	90	10	90	93	7	93
Harmonics	100	94	6	94	92	8	92	94	6	94
Total of accuracy rate			95.3 %			93 %			94.5%	

results between WSVM and ANN is shown in Table 1. WSVM has a higher correct identification rate than the method based on Probabilistic Neural Network.

CONCLUSION

The experimental results showed that the proposed method has the ability of recognizing and classifying different power disturbance types efficiently and it has the potential to enhance the performance of the power transient recorder with real-time processing capability. Because the distorted signals in this study were generated by MatLab, employing real distorted signals measured by the digital recorder to improve the proposed method is one of our future works. The further research is about to focus on comparing DOST with Multiwavelets, Ridgelets as feature extractors.

REFERENCES

Arrillaga J., N.R. Watson and S. Chen, 2000. Power System Quality Assessment. John Wiley and Sons. 1st Edn., pp: 312. ISBN: 978-0-471-98865-6.

Bollen, M.H.J., 2000. Understanding Power Quality Problems-Voltage Sags and Interruptions. Wiley-IEEE Press, New York. 1st Edn., pp: 672. ISBN: 978-0-7803-4713-7.

Burges, C.J.C., 1998. A Tutorial on Support Vector Machines for Pattern Recognition. J. Data Mining and Knowledge Discovery, 2(2): 121-167. ISSN:1384-5810, Doi: 10.1023/A:1009715923555, Kluwer Academic Publishers.

Gaouda, A.M., M.M.A. Salama, M.R. Sultan and A.Y. Chikhani, 1999. Power quality detection and classification using wavelet multiresolution signal decomposition. IEEE Trans. Power Delivery, 14: 1469-1476, Doi: 10.1109/61.796242.

Lin, C.J. and C.W. Hsu, 2002. A comparison of methods for multiclass Support vector machines. IEEE Trans. Neural Networks, 13: 415-425. Doi: 10.1109/72.991427.

Mitra, S., S.K. Pal and P. Mitra, 2002. Data mining in Soft Computing framework: A Survey. IEEE Trans. Neural Networks, 13: 3-14. Doi: 10.1109/72.977258.

Reddy, J.B., D.K. Mohanta and B.M. Karan, 2004. Power system disturbance recognition using wavelet and s-transform techniques. Int. J. Emerging Electric Power Syst., 1 (2). ISSN: 1553-779X.

Santoso, S., E.J. Powers, W.M. Grady and P. Hoffmann, 1996. Power quality assessment via wavelet transform analysis. IEEE Trans. Power Delivery, 11: 924-930. ISSN: 0885-8977, Doi: 10.1109/61.489353.

Santoso, S., E.J. Powers and W.M. Grady, 1997. Power quality disturbance data compression using wavelet transform methods, IEEE Trans. Power Delivery, 12: 1250-1257. Doi: 10.1109/61. 637001.

Stockwell, R.G., L. Mansinha and R.P. Lowe, 1996. Localization of the complex spectrum: The S-transform. IEEE Trans. Signal. Processing, 44: 998-1001. Doi: 10.1109/78. 492555.

Stockwell, R.G., L. Mansinha and R.P. Lowe, 1997a. Pattern analysis with two dimensional spectral localization: Applications of 2 dimensional S-Transforms. Elsevier Journal: Physica A: Statistical Mechanics and Its Applications, 239: 286-295. ISSN: 0378-4371.

Stockwell, R.G., L. Mansinha, R.P. Lowe, M. Eramian and R.A. Schincariol, 1997b. Local S Spectrum analysis of 1-D and 2-D data. Elsevier Journal: Physics of the Earth and Planetary Interiors, 103: 329-336. Doi: 1997 PEPI..103..329M.

Stockwell, R.G., 2007. A basis for efficient representation of the S-transform Elsevier. J. Digital Signal Processing, 17 (1): 371-393. ISSN:1051-2004.

Vetrivel, A., J. Jerome and N. Malmurugan, 2007. Artificial Intelligence and Signal Processing tools for classification of power quality events. A Survey National J. Tech., 3 (3): 18-28.

Zhang, L., W. Zhou and L. Jiao, 2004. Wavelet Support Vector Machine, IEEE Trans. Syst. Man and Cybernetics-Part B: Cybernetics, 34 (1): 34-39. Doi: 10.1109/TSMCB.2003.811113.