A Comparative Study of Feature Extraction Techniques for Power Disturbances Pattern Recognition using SVMs

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Abstract

The rapid increase in computer technology and the availability of large scale power quality monitoring data should now motivate distribution network service providers to attempt to extract information that may otherwise remain hidden within the recorded data. Such information may be critical for identification and diagnoses of power quality disturbance problems, prediction of system abnormalities or failure, and alarming of critical system situations. Data mining tools are an obvious candidate for assisting in such analysis of large scale power quality monitoring data. Firstly feature extraction technique is employed to extract features from raw power quality data. Finally support vector machine is used as a data mining tool to classify the extracted features into different disturbance type. Feature extraction technique should be efficient for the effective functioning of data mining tool. In this work, two methods of feature extraction for Power quality data mining are studied: Discrete Wavelet Transform (DWT) and S-Transform (Phase Corrected DWT). The S-transform requires less number of features as compared to wavelet based approach for the identification of PQ events. Since the proposed feature extraction technique can reduce the dimensionality of the disturbance signal to a great extent without losing its original property, less memory space and learning SVM time are required for classification.

Keywords—data mining, Power quality, s-transform, support vector machine, wavelet transform

I. Introduction

Due to the high level of uncertainty with regard to power system network, along with multidimensional parameters such as voltage, current and impedance, utility engineers are now beginning to rely on the classification tools of data mining techniques to support decisions of assessing the quality of operation of power systems. 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]. This requires continuous monitoring of voltage and current waveforms and their instantaneous values sampled 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. All these factors have prompted the need for intelligent data analysis methodologies, which could discover useful knowledge from raw power quality disturbance data. How to extract features of disturbances from a large number of power signals and how to recognize them automatically are important for further understanding

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and improving power quality. The data mining techniques for classification may lead to a poor classification accuracy rate when the training samples are not adequate[1-8]. This paper analyses and compares the performance of the two feature extraction methods, the wavelet transform and S-transform for power quality data mining. Although wavelet transform (WT) has the capability to extract information from the signal in both time and frequency domain simultaneously and has been applied in the detection and classification of power quality[2,5], it also exhibits some disadvantages, such as its complicated computation, sensitivity to noise level, and the dependency of its accuracy on the chosen basis wavelet . The S-transform (ST) [1,9]on the other hand, can be seen as an extension of ideas of WT and it has characteristics superior to WT. The excellent time-frequency resolution characteristic of the S-transform makes it an attractive candidate for analysis of power system disturbance signals. Several power quality problems are analyzed using both the S-transform and discrete wavelet transform, showing clearly the advantage of the S-transform in detecting, localizing, and classifying the power quality problems.

2. Feature Extraction Using Dwt

A. *Wavelet Analysis*

Wavelet analysis is a technique for carving up function or data into multiple components corresponding to different frequency bands. This allows one to study each component separately. Wavelet analysis is a form of time-frequency technique as it evaluates signal simultaneously in the time and frequency domains [4]. It uses wavelets, "small waves," which are functions with limited energy and zero average,

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \qquad (1)$$

The functions are typically normalized, $\|\psi\| = 1$ and centered in the neighborhood of $t = 0$. It plays the same role as the sine and cosine functions in the Fourier analysis. In wavelet transform, a specific wavelet is first selected as the basis function commonly referred to as the mother wavelet. Dilated (stretched) and translated (shifted in time) versions of the mother wavelet are then generated [2]. Dilation is denoted by the scale parameter a while translation is adjusted through b

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

where a is a positive real number and b is a real number. The wavelet transform of a signal $f(t)$ at a scale a and time translation b is the dot product of the signal $f(t)$ and the particular version of the mother wavelet, $\psi_{a,b}(t)$. It is computed by circular convolution of the signal with the wavelet function

$$w\{f(a,b)\} = \langle f, \psi_{a,b} \rangle = \int_{-\infty}^{+\infty} f(t) \cdot \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (3)$$

A contracted version of the mother wavelet would correspond to high frequency and is typically used in temporal analysis of signals, while a dilated version corresponds to low frequency and is used for frequency analysis. With wavelet functions, only information of scale $a<1$ corresponding to high frequencies is obtained. In order to obtain the low-frequency information necessary for full representation of the original signal $f(t)$, it is necessary to determine the wavelet coefficients for scale $a>1$.This is achieved by introducing a scaling function $\hat{\sigma}(t)$ which is an aggregation of the mother wavelets $\psi(t)$ at scales greater than 1.The scaling function can also be scaled and translated as the wavelet function,

$$\phi_{a,b}(t) = \frac{1}{\sqrt{a}}\phi\left(\frac{t-a}{b}\right) \qquad (4)$$

with scaling function, the low-frequency approximation of f(t) at a scale a is the dot product of the signal and the particular scaling function [3], and can be computed by circular convolution given by (5).

$$L\{f(a,b)\}=\langle f,\psi_{a,b}\rangle=\int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\phi\left(\frac{t-a}{b}\right)dt \quad (5)$$

Implementation of these two transforms (3) and (5) can be done smoothly in continuous wavelet transform (CWT) or discretely in discrete wavelet transform (DWT).

B. *Multiresolution Analysis*

One important trait of wavelet transform is that its nonuniform time and frequency spreads across the frequency plane. They vary with scale a but in the opposite manner, with the time spread being directly proportional to a while frequency spread to $1/a$. The resolutions of DWT vary across the planes. At low frequency when the variation is slow, the time resolution is coarse while the frequency resolution is fine. This enables accurate tracking of the frequency while allowing sufficient time for the slow variation to transpire before analysis. On the contrary, in the high-frequency range, it is important to pinpoint when the fast changes occur. The time resolution is therefore small, but the frequency resolution is compromised. This adjustment of the resolutions is inherent in wavelet transform as the wavelet basis is stretched or compressed during the transform [4]. This ability to expand function or signal with different resolutions is termed as multiresolution analysis, which forms the cornerstone of many wavelet applications.

In this sense, a recorder-digitized function $a_0(n)$, which is a sampled signal of $f(t)$, is decomposed into its smoothed version $a_1(n)$ (containing low-frequency components), and detailed version (containing higher-frequency components) $d_1(n)$, using filters $h(n)$ and $g(n)$, respectively. This is first-scale decomposition. The next higher scale decomposition is now based on signal $a_1(n)$ and so on (Fig. 2).

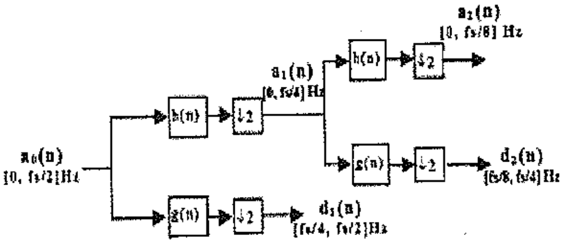

Figure 1. Multiresolution signal decomposition.

C. *Classification of Various Power Quality Events*

The Daubauchie "db4" wavelet function was adopted to perform the DWT. The different levels of wavelet coefficient over the scales can be interpreted as uneven distribution of energy across the multiple frequency bands [2,5]. This distribution forms patterns that have been found to be useful for classifying between different power quality events. If the selected wavelet and scaling functions form an orthonormal (independent and normalized) set of basis, then the Parseval theorem relates the energy of the signal to the values of the coefficients. This means that the norm or energy of the signal can be separated according to the following multiresolution expansion

$$\int |f(t)|^2 dt=\sum_k |A_{j0}(k)|^2+\sum_{j\leq j0}\sum_k |D_j(k)|^2 \quad (6)$$

These squared wavelet energy coefficients were shown to be useful features for identifying power quality events.

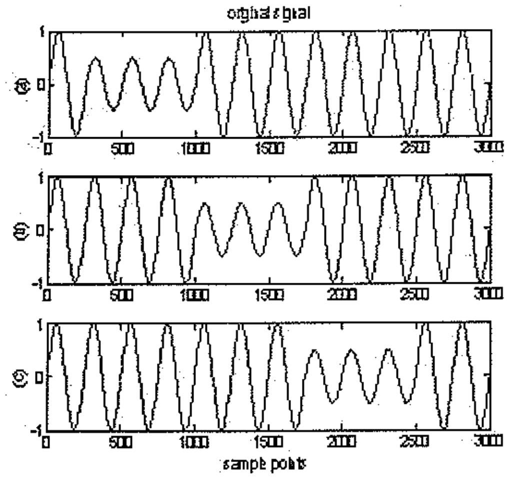

Figure 2 : Sag at different instants

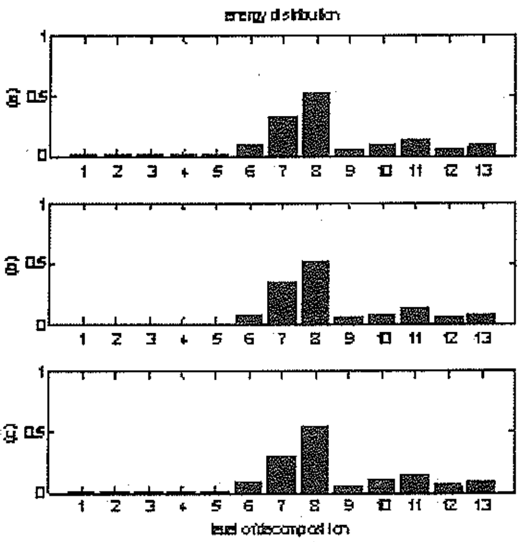

Figure 3 : Energy distribution diagram for sag at different instants

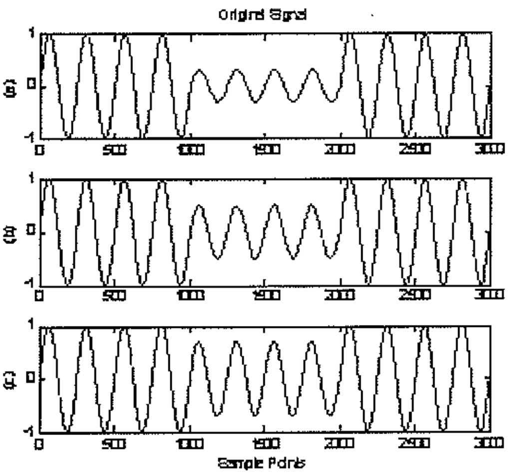

Figure 4. Sag with different amplitudes

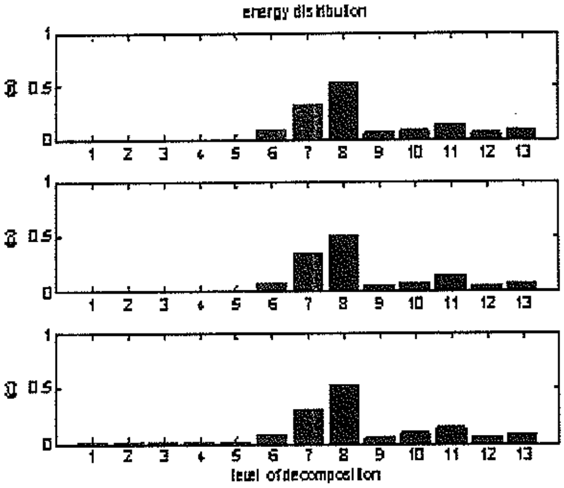

Figure 5. Energy distribution diagram for sag with different amplitudes

The properties of energy disturbance features are

- The energy distribution remains unaffected by the time of disturbance occurrence.
- The outline of energy distribution remains the same despite variations in the amplitude of the same disturbance type.

Figure 3 and 5 shows that the energy distribution pattern remains the same for the event sag despite occurring at different instants and with different amplitudes.

D. *Duration of Transients*

In general, when a transient disturbance occurs, the stable power signal will generate a discontinuous state at the start and end points of the disturbance duration. The wavelet coefficients generate severe variation at the start and end points of the disturbance [2]. Therefore, we can easily obtain the start time and end time of the disturbance from the variations in absolute wavelet coefficients and calculate the disturbance duration. Fig 6 shows the plot of level 1, level 2 and level 3 DWT coefficients for the disturbance swell. The coefficients show variation for the disturbance swell but there is no variation for pure sine wave in fig 7 because the signal is smooth.

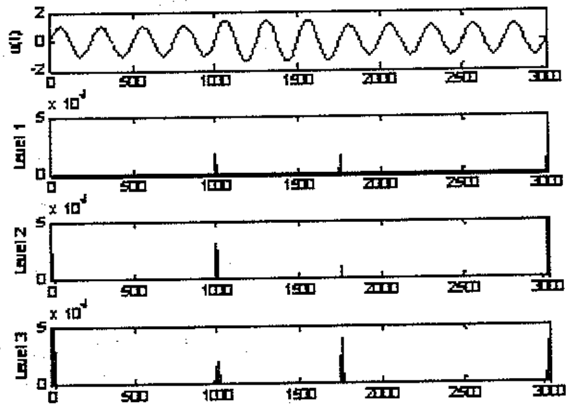

Figure 6 : Plot of DWT coefficients for swell

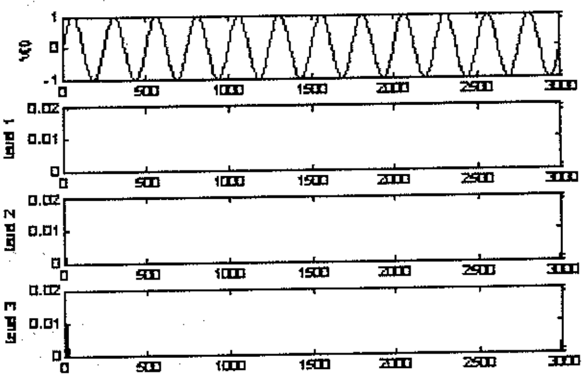

Figure 7 : Plot of DWT coefficients for sine

3. Feature Extraction Using S-transform

A. The Discrete S-Transform

Let $p[KT]$,k=0,1,..N-1 denotes a discrete time series corresponding to a signal p (t) with a time sampling interval of T. The discrete Fourier transform of the signal can be obtained as follows:

$$P\left[\frac{n}{NT}\right] = \frac{1}{N}\sum_{k=0}^{N-1} p[kT]e^{-(i2\Pi nk/N)} \tag{7}$$

where n=0, 1,...N-1 and inverse discrete Fourier transform is

$$p[kT] = \sum_{n=0}^{N-1} P\left[\frac{n}{NT}\right]e^{i2\Pi nk/N} \tag{8}$$

In the discrete case, the S-Transform is the projection of the vector defined by the time series p [kT], onto a spanning set of vectors [1,9].The spanning vectors are not orthogonal and the elements of the S-Transform are not independent. Each basis vector (of the Fourier transform) is divided into N localized vectors by an element- by- element product with the N shifted Gaussians, such that the sum of these N localized vectors is original basis vector. The S-Transform is given by

$$S\left[\frac{n}{NT}, jT\right] = \sum_{m=o}^{N-1} P\left[\frac{m+n}{NT}\right]G(n,m)e^{i2\Pi mj/N} \tag{9}$$

where $G(n,m) = e^{-(2\Pi^2 m^2/n^2)}$ =Gaussian function and

j,m, n = 0,1,....,N-1.

Steps for computing the discrete S-Transform

1) Perform the discrete Fourier transform of the original time series $p[kT]$ with N points and sampling interval T to get $P[m/NT]$ using the FFT routine. This is only done once.

2) Calculate the localizing Gaussian $G(n,m)$ for the required frequency n/NT.

3) Shift the spectrum $P[m/NT]$ to $P[(m+n)/NT]$ for the frequency n/NT (one pointer addition)

4) Multiply $P[(m+n)/NT]$ by $G[n,m]$ to get B[n/NT, m/NT] (N multiplications)

5) Inverse Fourier transform of $B[n/NT,m/NT]m/NT$ to j to give the row of $S[n/NT,jT]$ corresponding to the frequency n/NT

6) Repeat steps 3, 4, and 5 until all the rows of $S[n/NT,jT]$ corresponding to all discrete frequencies n/NT have been defined

From (9), it is seen that the output from the S-Transform is an N×M matrix called the S-matrix whose rows pertain to frequency and columns to time. Each element of the S-matrix is complex valued.

B. *Feature Extraction Using S-Transform*

The S-transform performs multiresolution analysis on a time varying signal as its window width varies inversely with frequency. This gives high time resolution at high frequency and high frequency resolution at low frequency. Since power quality disturbances make the power signal a nonstationary one, the S-Transform can be applied effectively. In this paper, the signals are simulated using MATLAB [3]. The signals are sampled at 256 points per cycle. Five types of power quality disturbances are simulated and the features of all the types of disturbances are extracted from the S-matrix. Further, from the S-matrix important information in terms of magnitude, phase and frequency can be extracted. These are shown in Figs. 8-10(a)–(d). The time-frequency contours of the S-transform output shows a decrease or increase in magnitude for voltage sag and swell, and interruption , which provide a better visual classification strategy in comparison to the wavelet transform (similar to time versus rms or peak value of voltage). It is observed that the standard deviation of second contour is an important parameter to distinguish between transients, impulses, and notches

Feature extraction is done by applying standard statistical techniques onto the S-matrix. Since, the aim is to obtain a satisfactory classification accuracy features based on standard deviation (S.D.) and energy of the transformed signal are extracted as follows.

Feature 1: Standard deviation (S.D.) of the data set comprising of the elements corresponding to maximum magnitude of each column of the S-matrix.

Feature 2: Energy of the data set comprising of the elements corresponding to maximum magnitude of each column of the S- matrix.

Feature 3: Standard deviation (S.D.) of the data set values corresponding to maximum value of each row of the S-matrix.

Feature 4: Standard deviation (S.D.) of the phase contour.

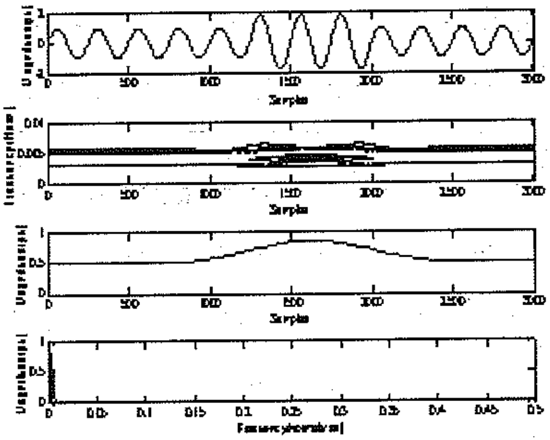

Figure 8 : Voltage Swell

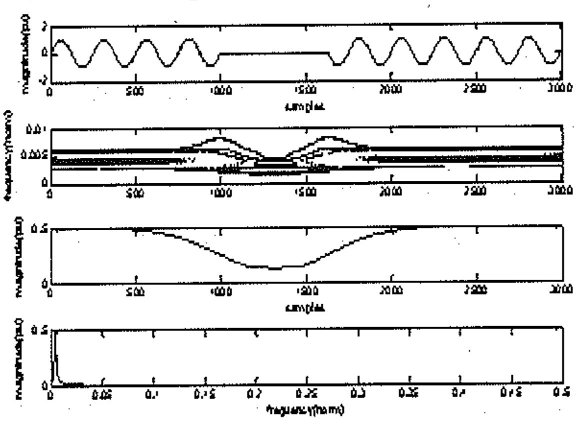

Figure 9 : Voltage interruption

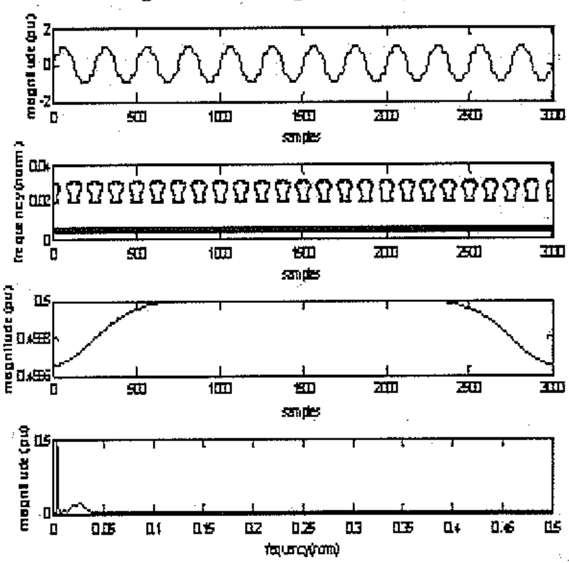

Figure 10 : Voltage Harmonics

4. Disturbances Classification Using SVM

In recent years, a new approach to construct and train neural networks (NNs) was developed, which is free of such disadvantages. The new networks are called SVMs. Support vector machines (SVMs) [10-14] were originally designed for binary classification. How to effectively extend it for multiclass classification is still an ongoing research issue. Currently there are two types of approaches for multiclass SVM. One is by constructing and combining several binary classifiers while the other is by directly considering all data in one optimization formulation. In general, it is computationally more expensive to solve a multi-class problem than a binary problem with the same number of data. This work is devoted to the second approach, i.e. it solves a multi-class problem by decomposing it to several binary problems in a hierarchical way. The three methods considered in this paper are "one-against-all" and "one-against-one" and "dendogram based SVM".

A. *One against all method*

The earliest used implementation for SVM multiclass classification is probably the one-against-all method (for example, [10]). It constructs k SVM models where k is the number of classes. The ith SVM is trained with all of the examples in the ith class with positive labels, and all other examples with negative labels. Thus given l training data, $(x_1,y_1),\ldots.(x_l,y_l)$, where x_i ε R_n, $i=1,\ldots.l$ and y_k ε $\{1,\ldots,k\}$ is the class of x_i, the ith SVM solves the following problem:

$$\min_{w^i,b^i,\xi^i} \frac{1}{2}(w^i)^T w^i + C\sum_{j=1}^{l} \xi_j^i (w^i)^T$$
$$(w^i)^T \phi(x_j) + b^i \geq 1-\xi_j^i, \quad \text{if } y_j = i$$
$$(w^i)^T \phi(x_j) + b^i \leq -1+\xi_j^i, \text{ if } y_j \neq i$$
$$\xi_j^i \geq 0, j=1,\ldots,l \qquad (10)$$

where the training data x_i are mapped to a higher dimensional space by the function ô and C is the penalty parameter. We say x is in the class which has the largest value of the decision function

$$\text{Class of } x \equiv \arg\max_{i=1,..k}((w^i)^T \phi(x) + b^i) \qquad (11)$$

B. *One against one method*

This method constructs $k(k\text{-}1)/2$ classifiers where each one is trained on data from the ith and jth classes, we solve the following binary classification problem:

$$\min_{w^{ij}b^{ij}\xi^{ij}} \frac{1}{2}(w^{ij})^T w^{ij} + C\sum_t \xi_t^{ij} (w^{ij})^T$$
$$(w^{ij})^T \phi(x_t) + b^{ij} \geq 1-\xi_t^{ij}, \quad \text{if } y_t = i$$
$$(w^{ij})^T \phi(x_t) + b^{ij} \leq -1+\xi_t^{ij}, \text{if } y_t = j$$
$$\xi_t^{ij} \geq 0 \qquad (12)$$

There are different methods for doing the future testing after all $k(k\text{-}1)/2$ classifiers are constructed. After some tests, the following voting strategy is used to determine the class. If sign $((w^{ij})^T \phi(x) + b^{ij}$ says that x is in the i[th] class, then the vote for the ith class is added by one. Otherwise, the j^{th} is increased by one. Then we predict x is in the class with the largest vote. The voting approach described above is also called the "Max Wins" strategy [10]. In case those two classes have identical votes, thought it may not be a good strategy, now we simply select the one with the smaller index. Since we have considered 5 classes of disturbances, the total number of SVMs are 10.

C. *Dendogram based SVM (DSVM)*

The proposed DSVM takes advantage of both the efficient computation of the ascendant hierarchical clustering of classes and the high classification accuracy of SVM for binary classification. Although DSVM needs (N-1) SVMs for N class problem in the training phase, for the testing phase DSVM requires an optimal set of SVMs selected in a descendant way from the root of the taxonomy through the selected class among the "leaf" nodes[11].

The first step of DSVM method consists of calculating N gravity centers for the N known classes. Then AHC clustering is applied over these N centers. Dendogram is constructed through the AHC 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 [11].

5. Application And Results

300 disturbance signals with 60 signals for each class were simulated using parametric equations in Matlab 7.3. The features extracted from wavelet and S-transform was applied to the SVM Classifiers for recognizing and classifying the distorted signals. The 10-Fold Cross Validation Evaluation Results of the wavelet and S-Transform based SVM Classifiers for the five data sets is shown in Table 2, 4.

Table1. Parametric equations for signal generation

Event	Equation
Pure Sinusoid	$v(t)=\sin(wt)$
Sag	$v(t)=1-\alpha_{ss}((1(t-t_1)-1(t-t_2)))\sin(wt)$
Swell	$v(t)=1+\alpha_{sw}((1(t-t_1)-1(t-t_2)))\sin(wt)$
Interruption	$v(t)=1-((1(t-t_1)-1(t-t_2)))\sin(wt)$
Harmonics	$v(t)=\begin{pmatrix}\alpha_{k1}\sin(wt)+\alpha_{k3}\sin(3wt)+\\ \alpha_{k5}\sin(5wt)+\alpha_{k7}\sin(7wt)\end{pmatrix}$
Flicker	$v(t)=(1+\alpha_f\sin(\beta_f wt))\sin(wt)$

Table 2.10-Fold Cross Validation Evaluation Result of the Wavelet Based Classifier

Class	One Against All	One Against One	DSVM
Sag	90	90	90
Swell	100	100	100
Interruption	70	90	90
Harmonics	100	100	100
Flicker	100	100	100
Overall	92	96	96

Table 3. Performance of Wavelet Based Classifier

Classifier	Training Time (sec)	Testing Time (sec)	Accuracy (%)
One Against One	0.7813	0.6563	96
One Against All	0.7969	0.2031	92
Dendogram SVM	0.6094	0.1875	96

Table 4.10-Fold Cross Validation Evaluation Result of the S-Transform Based Classifier

Class	One Against All	One Against One	DSVM
Sag	90	100	100
Swell	100	100	100
Interruption	80	90	90
Harmonics	100	100	100
Flicker	100	100	100
Overall	**94**	**98**	**98**

Table 5. Performance of S-Transform Based Classifier

Classifier	Training Time (sec)	Testing Time (sec)	Accuracy (%)
One Against One	0.6563	0.4563	98
One Against All	0.5469	0.17	94
Dendogram SVM	0.5	0.13	98

The test result shows that the S transform based SVM classifier attains better recognition rates when compared with the wavelet based SVM classifier.

6. Conclusion And Future Work

The numerical experiments performed for both Wavelet and S-Transform have confirmed that both solutions are very well suited for classification. S-Transform generates contours which are suitable for classification by simple visual inspection unlike wavelet transform that requires specific methods like Standard Multi Resolution Analysis for classification. Wavelet transform requires 13 features whereas S-transform requires only 4 features. The classification accuracy using s-Transform is very high and the training time is very less compared to wavelet transform. Further tests will be done on the signals produced from a realistic electrical power network.

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