Detection and Classification of Power Quality Disturbances Using S-Transform and Probabilistic Neural Network

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***Abstract*—This paper presents an S-Transform based probabilistic neural network (PNN) classifier for recognition of power quality (PQ) disturbances. The proposed method requires less number of features as compared to wavelet based approach for the identification of PQ events. The features extracted through the S-Transform are trained by a PNN for automatic classification of the PQ events. Since the proposed methodology can reduce the features of the disturbance signal to a great extent without losing its original property, less memory space and learning PNN time are required for classification. Eleven types of disturbances are considered for the classification problem. The simulation results reveal that the combination of S-Transform and PNN can effectively detect and classify different PQ events. The classification performance of PNN is compared with a feedforward multilayer (FFML) neural network (NN) and learning vector quantization (LVQ) NN. It is found that the classification performance of PNN is better than both FFML and LVQ.**

***Index Terms*—Detection and classification of power quality disturbances, probabilistic neural network (PNN), S-transform.**

I. Introduction

THE quality of electric power has become an important issue for electric utilities and its customers. As a result, power quality (PQ) study is gaining interest. Degradation in quality of electric power is normally caused by power-line disturbances such as voltage sag/swell with and without harmonics, momentary interruption, harmonic distortion, flicker, notch, spike and transients, causing problems such as malfunctions, instabilities, short lifetime, failure of electrical equipments and so on. In an electric distribution network faults may cause voltage sag or momentary interruption whereas switching off large load or energization of a large capacitor bank may lead to voltage swell. On the other hand, use of solid-state switching devices and nonlinear and power electronically switched loads such as rectifiers or inverters may cause harmonic distortion and notching in the voltage and current. Use of arc furnaces may lead to flickers. Ferroresonance, transformer energization, or capacitor switching may cause transients and lightning strikes may lead to spikes.

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In a realistic distribution system, in order to improve power quality, these disturbances need to be identified before appropriate mitigating action can be taken. Therefore, in this paper these 11 types of disturbances (normal waveform is also included for the classification from other disturbances) which occur frequently in a distribution network are considered.

One of the important issues in power quality analysis is to detect and classify disturbance waveforms automatically in an efficient manner. To detect, solve, and mitigate the PQ problem, many utilities perform PQ monitoring for their industrial and key customers. In the deregulated market, the PQ monitoring would be an effective means for providing better customer services as well as reinforcing competitiveness among the utilities.

In order to identify the type of disturbance present in the power signal effectively, several authors have presented different methodologies based on combination of wavelet transform (WT) and artificial neural network (ANN) [1]–[3]. Using the properties of WT and the features of the decomposed waveform along with ANN algorithm, it is possible to extract important information from a disturbance signal and determine the type of disturbance that caused power quality (PQ) problem to occur. The energy of the distorted signal will be partitioned at different resolution levels in different ways depending on the power quality problem in hand. The standard deviation can be considered as a measure of the energy of a signal with zero mean [4].

Gaing [2] has classified seven types of PQ events by using wavelets and probabilistic neural network (PNN). Energy distribution at 13 decomposition levels of wavelet and time duration of each disturbance are taken as features and applied to PNN for classification. Considering a large number of features may result in high memory and computational overhead.

Haibo *et al.* [3] has presented the classification of seven types of PQ disturbances by using a self organizing learning array system (based on wavelet transform) considering 11 features (energy at 11 decomposition levels). Besides, 22 families of wavelets are tested to identify the best one for a better classification.

Wavelet exhibits its notable capabilities for detection and localization of the disturbances [4]–[8]. However, its capabilities are often significantly degraded in real practice under noisy environment. On the other hand, S-Transform has the ability to detect the disturbance correctly in the presence of noise. This ability of S-Transform attracts the researchers for the detection and classification of PQ disturbances.

This paper presents a probabilistic neural network (PNN) classifier based on S-Transform [9] where less number of features i.e., four features are required for effective classification of 11 types of PQ disturbances. Since only four features are required, the memory requirement and computational time will reduce. Moreover, using S-Transform instead of wavelets will avoid requirement of testing various families of wavelet to identify the best one for a better classification. The superior properties of S-Transform can provide significant improvement in the detection of PQ disturbances [10]. The features extracted from S-Transform are given to the PNN for training and subsequently it is tested for an effective classification. The PNN [11], [12] can function as a classifier and has the advantage of being a fast learning process as it requires only a single-pass network training stage without any iteration for adjusting weights. Further, it can itself adapt to architectural changes. As the structure of PNN is simple and learning efficiency is very fast it is suitable for signal classification problems. The performance of PNN is compared with two other well-known neural networks i.e., feedforward multilayer back propagation (FFML) and learning vector quantization (LVQ). From the simulation results, it is found that the PNN classifies the PQ events more effectively than either FFML or LVQ. The paper is organized as follows.

In Section II, the discrete S-Transform is explained. Feature extraction by S-Transform is given in Section III and detection capability of S-transform is shown in Section IV. Theory and architecture of the PNN is given in Section V. Section VI deals with the classification of PQ disturbances by using PNN and Section VII deals with performance of PNN under noisy environment. Finally, conclusions are given in Section VIII.

II. The Discrete S-Transform

Let $p[kT]$, $k = 0, 1, \ldots, N-1$ denote 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:

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

where $n = 0, 1, \ldots, N-1$ and the inverse discrete Fourier transform is

$$p[kT] = \sum_{n=0}^{N-1} P\left[\frac{n}{NT}\right] e^{i2\pi nk/N}. \tag{2}$$

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 [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 of a discrete time series $p[kT]$, is given by [9]

$$S\left[\frac{n}{NT}, jT\right] = \sum_{m=0}^{N-1} P\left[\frac{m+n}{NT}\right] G(n,m)e^{i2\pi mj/N} \tag{3}$$

where $G(n,m) = e^{-(2\pi^2 m^2/n^2)}$ = Gaussian function and where $j, m, n = 0, 1, \ldots, N-1$.

The following steps are adapted for computing the discrete S-Transform [9].

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 (3), it is seen that the output from the S-Transform is an $N \times M$ matrix called the S-matrix whose rows pertain to frequency and columns to time. Each element of the S-matrix is complex valued. The choice of windowing function is not limited to the Gaussian function, other windowing functions were also implemented successfully [13].

III. 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 [14]. The sampling frequency is (64 $\times$ 50) i.e., 3.2 kHz. Eleven 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. 1 and 2 for the two types of disturbances i.e., voltage sag and voltage swell, respectively. For simplicity, only two disturbances (sag and swell) are shown here. In Fig. 1(a), the thick line is the locus of maximum value of the elements present in the column of the S-matrix corresponding to the time. Fig. 1(b) represents the frequency contour of the S-matrix, which gives the complete visualization of the voltage sag. Fig. 1(c) represents the maximum magnitude of each frequency components present in the signal. To determine the phase from the S-Matrix, the elements having maximum amplitude in a column is determined and the corresponding phase is calculated. The obtained phase is called stationary phase of the signal and its contour is shown in Fig. 1(d). Similarly, Fig. 2(a)–(d) represents the above described characteristics for a voltage swell disturbance.

Feature extraction is done by applying standard statistical techniques onto the S-matrix. Many features such as amplitude, slope (or gradient) of amplitude, time of occurrence, mean, standard deviation and energy of the transformed signal are widely

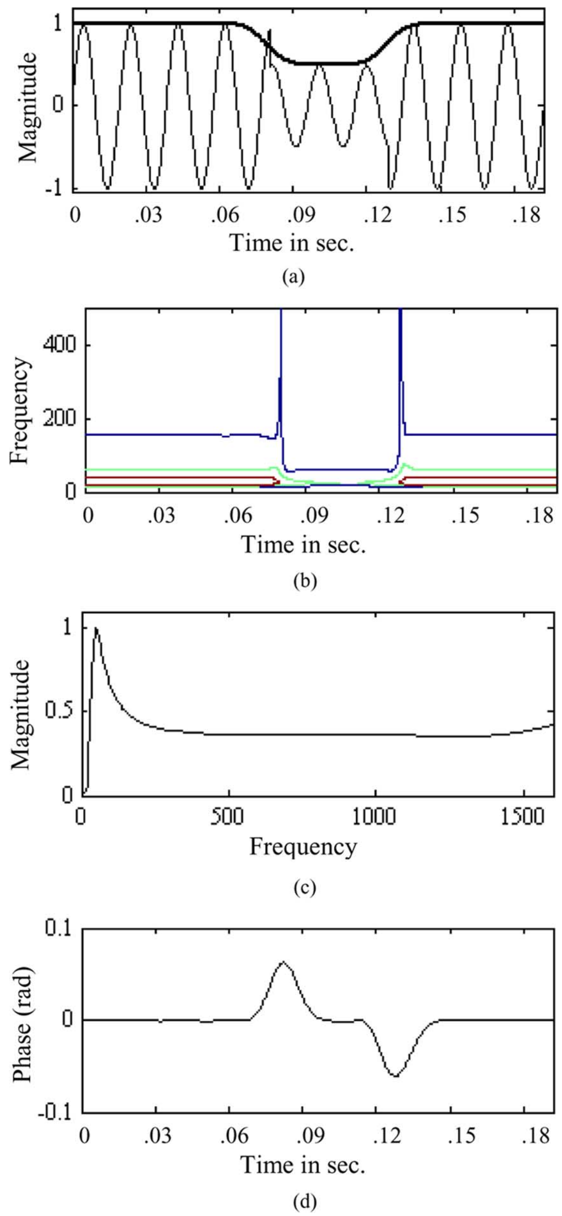

Fig. 1. Voltage sag and its feature waveforms.

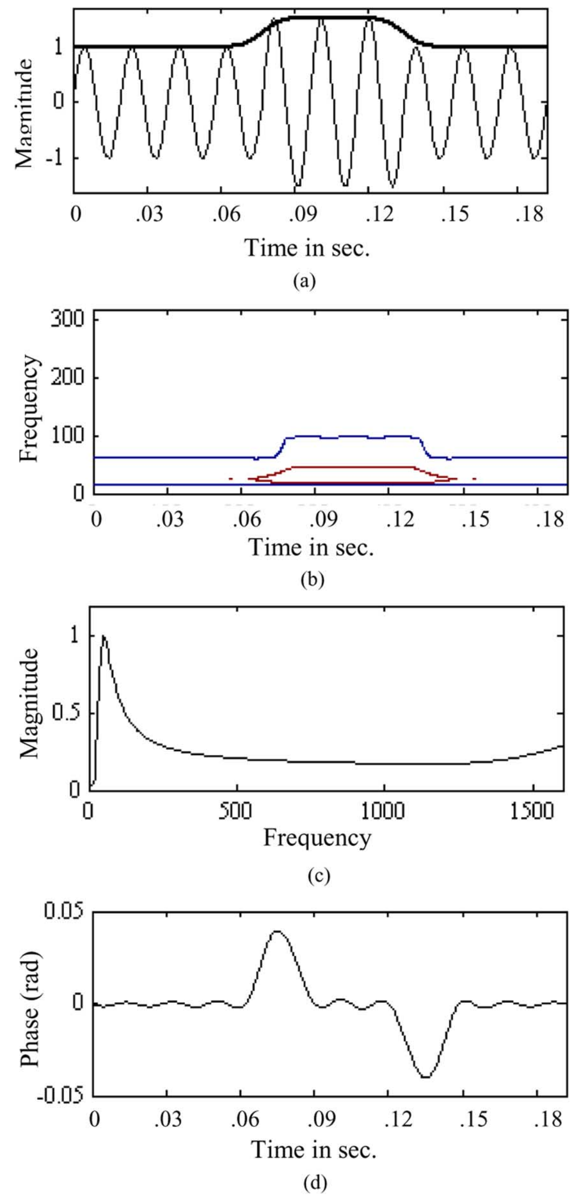

Fig. 2. Voltage swell and its feature waveforms.

used for proper classification. Since, the aim is to obtain a satisfactory classification accuracy one can try with some of the features listed above. In this paper, 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.

To visualize the suitability of these features for classification, a three-dimensional map comprising of S.D. of magnitude (Feature 1), energy of magnitude (Feature 2), and S.D. of frequency (Feature 3) is developed and shown in Fig. 3(a). From Fig. 3(a), it is clearly visible that except for classes namely C3, C6, and C7, others have separate classification surface. To overcome this overlapping between classes another feature i.e., S.D. of phase contour (Feature 4) is added and the three-dimensional plot comprising of S.D. of magnitude (Feature 1), S.D. of frequency (Feature 3) and S.D. of phase contour (Feature 4) is presented in Fig. 3(b). From Fig. 3(b), it is quite clear that the overlapping classes of Fig. 3(a) are now separated. Therefore, these four features based on S.D. and energy when combined together and given to a nonlinear classifier can classify the PQ disturbances accurately.

IV. Detection Capability of S-Transform

The S-Transform has an edge over the wavelet in detecting the occurrence of disturbance under noisy condition. This can be ascertained by considering following example. Consider the

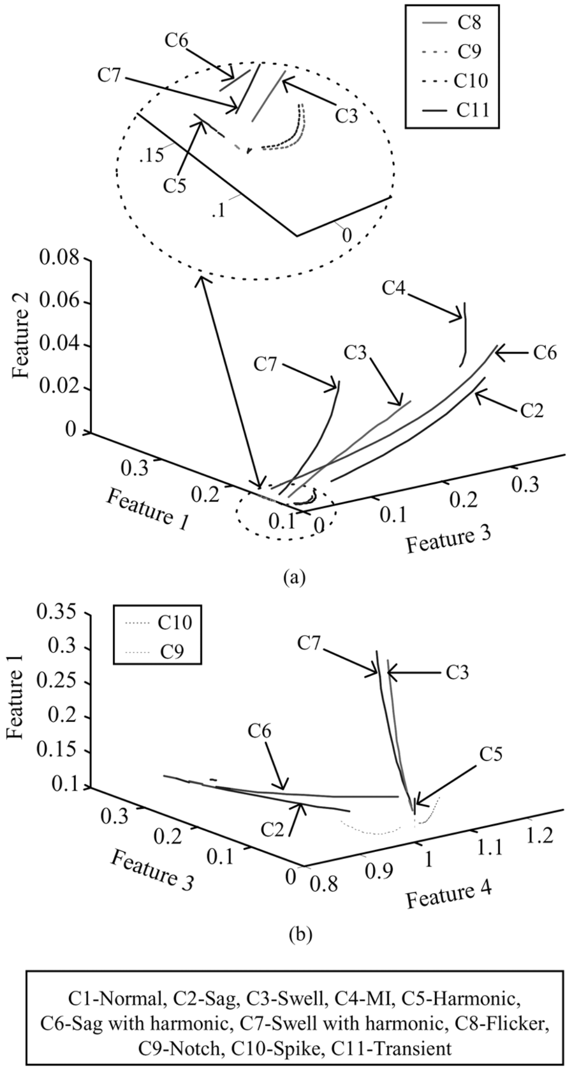

Fig. 3. Three-dimensional plot of features.

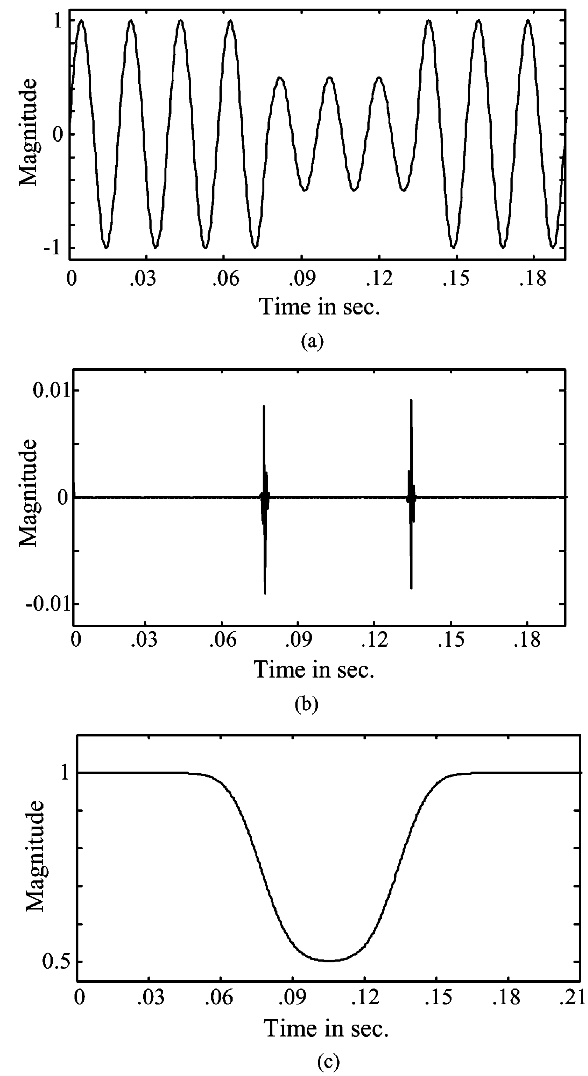

Fig. 4. (a) Voltage sag, (b) output of wavelet, and (c) output of S-Transform.

voltage sag disturbance without noise and with 20-dB noise as shown in Figs. 4(a) and 5(a), respectively. Figs. 4(b) and 5(b) show the plots of 1st decomposition level (which consists detection capability) of wavelet. When there is no noise in the signal, the wavelet can accurately detect the presence of disturbance, as shown in Fig. 4(b). However, when there is noise wavelet fails to detect which is depicted in Fig. 5(b). On the other hand, S-Transform can detect the disturbance correctly in both pure as well as noisy environments as shown in Figs. 4(c) and 5(c), respectively. Figs. 4(c) and 5(c) show the locus of maximum value of the elements present in the column of the S-matrix corresponding to the time as explained in Section III. Hence, it is clear that S-Transform has a better detection capability than that of the wavelet.

V. Probabilistic Neural Network (PNN)

The PNN model is one among the supervised learning networks and has the following features distinct from those of other networks in the learning processes [12].

- It is implemented using the probabilistic model, such as Bayesian classifiers.
- A PNN is guaranteed to converge to a Bayesian classifier provided that it is given enough training data.
- No learning processes are required.
- No need to set the initial weights of the network.
- No relationship between learning processes and recalling processes.
- The difference between the inference vector and the target vector are not used to modify the weights of the network.

The learning speed of the PNN model is very fast making it suitable in real time for fault diagnosis and signal classification problems. Fig. 6 shows the architecture of a PNN model that is composed of the radial basis layer and the competitive layer.

In the signal-classification application, the training examples are classified according to their distribution values of probabilistic density function (pdf), which is the basic principle of the PNN. A simple pdf is as follows:

$$f_k(X) = \frac{1}{N_k}\sum_{j=1}^{N_k}\exp\left(-\frac{\|X - X_{kj}\|}{2\sigma^2}\right). \tag{4}$$

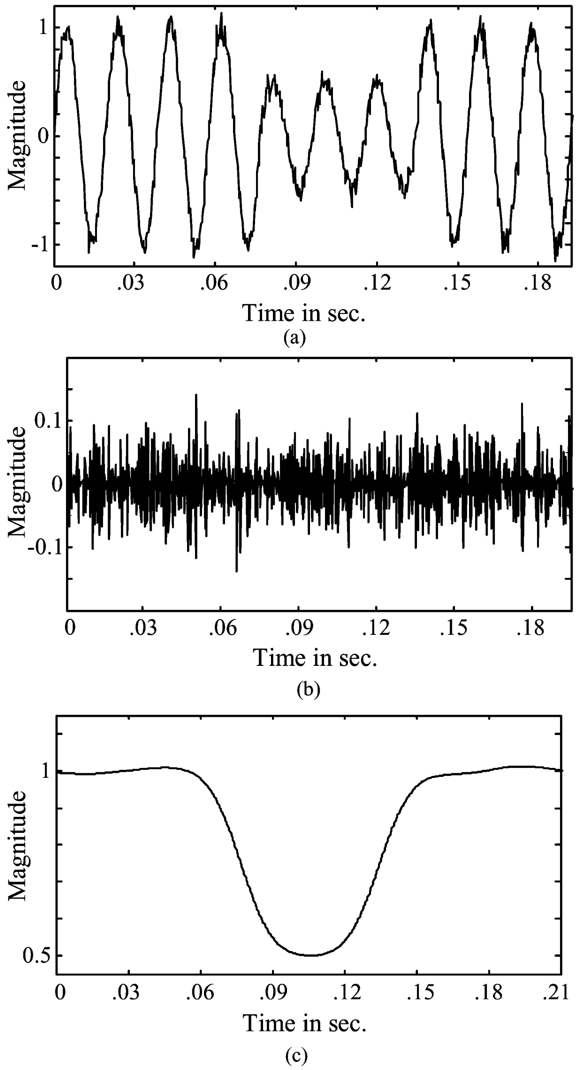

Fig. 5. (a) Voltage sag with 20-dB noise, (b) output of wavelet, and (c) output of S-Transform.

Modifying and applying (4) to the output vector H of the hidden layer in the PNN is as follows:

$$H_h = \exp\left(\frac{-\sum_i \left(X_i - W_{ih}^{xh}\right)^2}{2\sigma^2}\right) \tag{5}$$

$$\mathrm{net}_j = \frac{1}{N_j}\sum_h W_{hj}^{hy} H_h \text{ and } N_j = \sum_h W_{hj}^{hy};$$
$$\mathrm{net}_j = \max_k(\mathrm{net}_k) \text{ then } y_j = 1, \text{ else } y_j = 0 \tag{6}$$

where

i	number of input layers;
h	number of hidden layers;
j	number of output layers;
k	number of training examples;
N	number of classifications (clusters);
σ	smoothing parameter (standard deviation);
X	input vector;

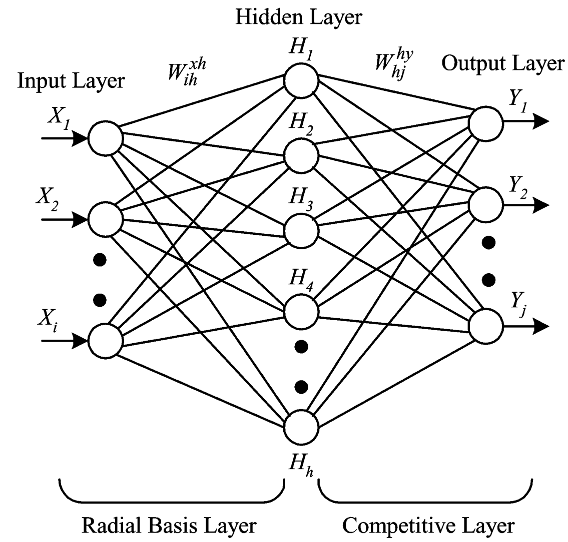

Fig. 6. Architecture of a PNN.

and where $\|X - X_{kj}\|$ is the Euclidean distance between the vectors X and X_{kj}, i.e., $\|X - X_{kj}\| = \sum_i (X - X_{kj})^2$; W_{ih}^{xh} is the connection weight between the input layer X and the hidden layer H; and W_{hj}^{hy} is the connection weight between the hidden layer H and the output layer Y.

The learning and recalling processes of the PNN for classification problems can be found in [12].

VI. Classification of PQ Disturbances Using PNN

Eleven classes $(C1 - C11)$ of different PQ disturbances are taken and are as follows:

C1 Normal
C2 Pure Sag
C3 Pure Swell
C4 Momentary Interruption (MI)
C5 Harmonics
C6 Sag with Harmonic
C7 Swell with Harmonic
C8 Flicker
C9 Notch
C10 Spike
C11 Transient

Based on the feature extraction by the S-Transform method, four-dimensional feature sets for training and testing are constructed. The dimensions here describe the different features derived from the S-Transform. All the data sets of features for various classes are applied to PNN for automatic classification of PQ events.

To evaluate the performance of PNN, its results are compared with the FFML network and a learning vector quantization (LVQ) network. LVQ is a supervised version of self-organizing map (SOM), suitable particularly for classification problems [15], [16]. At the outset, the performance analysis of LVQ, FFML, and PNN is carried out only for three classes i.e., normal, sag and swell for the classification. Each neural network is trained with 25 input data (or events) of each class and 100 data (or events) of each class are considered for testing.

TABLE I
CLASSIFICATION RESULTS OF LVQ, FFML AND PNN FOR THREE CLASSES

	LVQ			FFML			PNN		
	C1	C2	C3	C1	C2	C3	C1	C2	C3
C1 →	**100**	0	0	**100**	0	0	**100**	0	0
C2 →	12	**84**	4	0	**100**	0	0	**100**	0
C3 →	8	7	**85**	5	0	**95**	0	1	**99**
	Overall Accuracy= 90%			Overall Accuracy= 98%			Overall Accuracy= 99.6%		

TABLE II
CLASSIFICATION RESULTS OF LVQ, FFML, AND PNN FOR VARIOUS NUMBER OF CLASSES

Sr. No.	No. of classes	Overall classification accuracy		
		LVQ	**FFML**	**PNN**
1	3 classes (C1-C3)	90 %	98 %	99.6 %
2	5 classes (C1-C5)	84 %	94 %	99 %
3	7 classes (C1-C7)	68 %	93 %	98.75 %
4	11 classes (C1-C11)	51 %	88 %	97.4 %

TABLE III
CLASSIFICATION RESULTS OF FFML

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
C1 →	**89**	11	0	0	0	0	0	0	0	0	0
C2 →	0	**99**	1	0	0	0	0	0	0	0	0
C3 →	12	5	**75**	8	0	0	0	0	0	0	0
C4 →	0	2	2	**95**	0	0	0	1	0	0	0
C5 →	0	0	0	0	**96**	2	1	1	0	0	0
C6 →	0	0	0	0	9	**85**	6	0	0	0	0
C7 →	0	0	0	0	0	7	**90**	2	0	1	0
C8 →	0	0	0	0	0	0	8	**79**	9	4	0
C9→	0	0	0	0	1	0	0	0	**99**	0	0
C10→	0	2	0	2	0	0	0	1	2	**89**	4
C11→	0	0	0	0	0	0	0	0	26	2	**72**
Overall Accuracy: 88%											

The classification results during testing are shown in Table I. The diagonal elements (shown by bold letters) represent correctly classified PQ events. Off-diagonal elements represent the misclassification. The overall accuracy of correct classification is the ratio of correctly classified events to that of the total number of events. The overall classification accuracy for LVQ, FFML, and PNN is 90%, 98%, and 99.6%, respectively (Table I). Hence, PNN gives the best classification results for this case. With the same data, these networks are trained and subsequently tested for higher number of classes. The testing results are shown in Table II. From Table II, it is seen that as number of classes increases the overall classification accuracy of LVQ and FFML degrades with LVQ performing the worst. On the other hand, classification performance of PNN is excellent even for 11 number of classes. The individual and overall classification for FFML and PNN with 11 number of classes are shown in Tables III and IV, respectively. Here, FFML is optimized for number of hidden neurons in all the cases and statistics is given in Table V.

Classification accuracy can be further enhanced by training the PNN by higher number of events. Table VI shows the testing results when training events are made double (50 events for each class). From Table VI, it is seen that testing accuracy enhances to 98.64%.

TABLE IV
CLASSIFICATION RESULTS OF PNN

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
C1 →	**100**	0	0	0	0	0	0	0	0	0	0
C2 →	1	**95**	0	4	0	0	0	0	0	0	0
C3 →	9	0	**91**	0	0	0	0	0	0	0	0
C4 →	1	0	0	**99**	0	0	0	0	0	0	0
C5 →	2	0	0	0	**96**	0	0	2	0	0	0
C6 →	0	0	0	1	1	**98**	0	0	0	0	0
C7 →	1	0	1	0	0	0	**98**	0	0	0	0
C8 →	1	0	0	0	1	0	0	**98**	0	0	0
C9 →	1	0	0	0	0	0	0	0	**99**	0	0
C10→	1	0	0	0	0	0	0	0	1	**98**	0
C11→	0	0	0	0	0	0	0	0	0	0	**100**
Overall Accuracy: 97.4%											

TABLE V
OPTIMIZED VALUES OF HIDDEN NEURONS FOR FFML

No. of classes	3 classes (C1-C5)	5 classes (C1-C5)	7 classes (C1-C7)	11 classes (C1-C11)
No. of hidden neurons	10	15	25	30

TABLE VI
CLASSIFICATION WITH INCREASED TRAINING EVENTS

Total training events	Overall classification accuracy of testing events
275 (25 for each class)	97.4 %
550 (50 for each class)	98.64 %

To demonstrate the uncertainty handling capability of the PNN classifier, it is trained and tested with reduced number of features (i.e., first three features as stated in Section III). The comparative results with 4 features and 3 features are shown in Table VII in which only correctly classified events are given. The overall accuracy (= correctly classified events divided by total number of events) with three features is 95.91%. Hence, even by using three features, PNN gives good accuracy of classification. This result also justifies the selection of features as stated in Section III.

It should be noted that the structure of PNN is simple and it requires less number of learning epochs and less learning time as compared to FFML as presented in Table VIII. Similarly, PNN requires much less time to classify a particular input data during testing as specified in Table VIII. Hence, it is clarified that with the four features resulting from S-Transform, a PNN can effectively classify different kinds of PQ disturbances.

VII. PERFORMANCE OF PNN UNDER NOISY ENVIRONMENT

In an electrical power distribution network, the practical data consists of noise; therefore, the proposed approach has to be analyzed under noisy environment. Gaussian noise is widely considered in the research of power quality issues. In actual prac-

TABLE VII
COMPARISON OF ACCURACIES WITH THREE AND FOUR FEATURES

Class	Classification Accuracy (in percentage)	
	With 3 features	With 4 features
C1	99	100
C2	96	95
C3	87	91
C4	100	99
C5	87	96
C6	98	98
C7	99	98
C8	92	98
C9	99	99
C10	98	98
C11	100	100
Overall Accuracy	**95.91**	**97.4**

TABLE VIII
COMPARATIVE ANALYSIS OF PERFORMANCE OF PNN AND FFML

	PNN	Feed forward FFML
Learning epochs	1	1000
Training CPU time (sec)	0.9	75
Testing CPU time (sec)	0.002	0.06

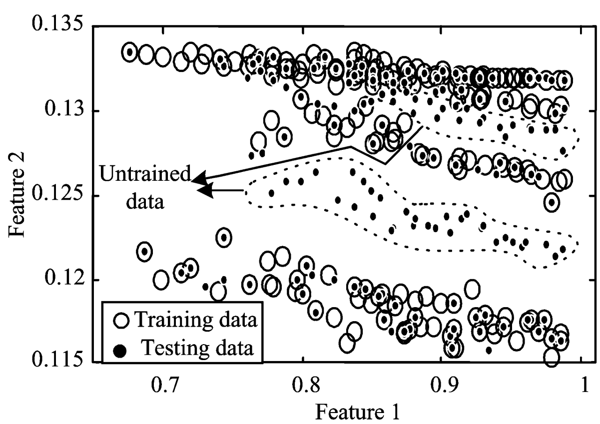

Fig. 7. Training and testing data for sag under noisy condition.

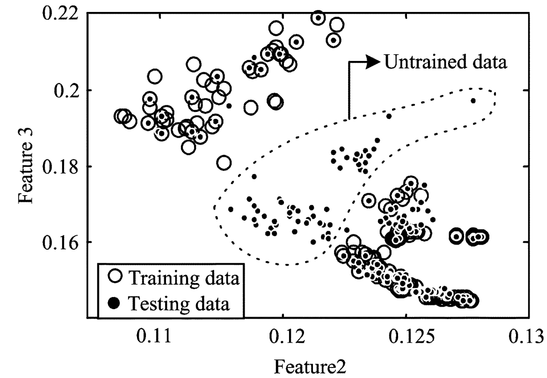

Fig. 8. Training and testing data for transient under noisy condition.

TABLE IX
CLASSIFICATION RESULTS OF PNN WITH NOISY DATA ADDED WITH PURE

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
C1 →	**94**	0	0	0	2	0	0	4	0	0	0
C2 →	0	**98**	0	0	0	0	0	0	0	2	0
C3 →	0	0	**92**	0	0	0	0	3	0	3	2
C4 →	1	0	0	**99**	0	0	0	0	0	0	0
C5 →	0	0	0	0	**95**	0	4	1	0	0	0
C6 →	0	0	0	0	2	**98**	0	0	0	0	0
C7 →	1	0	10	0	5	0	**84**	0	0	0	0
C8 →	3	0	0	0	0	0	0	**82**	0	0	15
C9 →	0	0	0	0	0	0	0	0	**99**	0	1
C10→	0	0	0	0	0	0	0	0	0	**99**	1
C11→	2	0	0	0	0	0	0	11	1	0	**86**
Overall Accuracy: 93.2%											

tice, since noise is a random parameter, the noise with which NN is trained may not be same when NN classifier is installed for testing. Hence, PNN is trained and tested with different noise level signals.

The noise is added with pure signals and operated with S-Transform for the feature extraction. Then with these features PNN is trained and subsequently tested for automatic classification. The PNN is trained with noisy signals consisting of signal to noise ratio (SNR) 20, 30, and 40 dB and tested with 20, 25, 30, 35, and 40 dB noise levels. Figs. 7 and 8 show the representation of training and testing events for sag and transient respectively. For simplicity, events of only two classes are shown. From Figs. 7 and 8, it is quite clear that a cluster of events (represented within highlighted region that corresponds to 25 and 35 dB noise levels) are present during testing phase which are not included during training. The classification results are shown in Table IX. The overall accuracy is 93.2% which reflects the extrapolating capability of PNN. Hence, classification results of PNN are satisfactory even if noise levels are different during training and testing.

VIII. CONCLUSIONS

In this paper, an attempt has been made to extract efficient features of the PQ disturbances using S-Transform. It is observed that these features correctly classify the PQ disturbances, even under noisy conditions, as these features are based on magnitude, frequency, and phase of the disturbance signal. This has advantage over wavelet analysis in which some of the features are noise prone (like the energy at dilation levels 1 and 2) and a de-noising scheme is to be implemented to extract those features accurately.

It is observed that the PNN correctly classifies the PQ class with high accuracy. The PNN is compared with both LVQ and FFML and it is found that PNN gives the best result. Therefore, the proposed method can be used as a power quality event classifier.

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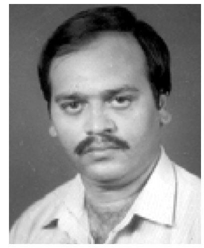

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