Electrical Power Quality and Utilisation, Journal Vol. XVII, No. 2, 2014

Application of Two Dimensional Wavelet Transform for Classification of Power Quality Disturbances

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Summary: Identification of voltage and current disturbances is an important task in power system monitoring and protection. In this paper, the application of two-dimensional wavelet transform for characterization of a wide variety range of power quality disturbances is discussed, and a new algorithm, based on image processing techniques is proposed for this purpose. A matrix is formed based on a specified number of cycles in such a way that the samples of voltage signal in each cycle form one row of that matrix. This matrix can be regarded as a two dimensional image. A two-dimensional wavelet transform is used to decompose the image into approximation and details, which contain low frequency and high frequency components along the rows and columns, respectively. Different disturbances result into different special patterns in detail images. By processing the detail images, specific features are defined which can suitably discriminate various types of disturbances. Combination of the feature generation algorithm and a classifier system leads to a smart system for classification of wide variety range of disturbances.

Keywords:
Power quality,
Event Detection and Classification,
Two Dimensional Wavelet Transform,
Pattern classification,
Image processing,
Feature,
Classifier system

1. INTRODUCTION

Rapid developments of power electronic devices and their widespread application in industry have brought the following two concerns. From one hand, these devices are major sources of power quality problems, and from the other hand, they are much more sensitive to voltage disturbances than their counterparts in the past [16, 21].

Therefore, Industries with sensitive electrical loads have become more dependent on the quality of power supply systems, and the electric power quality has become an important issue for electric utilities and their customers. The quality of a power supply is largely synonymous with the voltage quality. To improve electric power quality, sources and causes of disturbances must be specified before taking any mitigating action. In order to achieve this purpose, it is essential to monitor and then classify the events [4, 9].

Most of the disturbances can be detected and classified by just examining the waveforms with an expert eye. However, this procedure may become difficult and time-consuming when the volume of the recorded data increases. Therefore, it becomes desirable to do this process automatically and specific rules and tools must be developed for this purpose.

Several methods are reported which use Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT) to characterize steady state and transient power quality disturbances [7, 13, 14, 20]. Each of these approaches has its own shortcomings. For example, disturbance detection based on one dimensional DWT has the shortcoming of detecting steady state disturbances and disturbances of slow nature [10]. Therefore, new tools are investigated which are capable of detecting and classifying transients and high frequency disturbances, besides low frequency and steady state disturbances.

In [11], a novel two dimensional representation of power quality data is proposed based on which two dimensional analysis tools can be applied. Based on this representation, the authors have proposed a new approach for detecting power quality disturbances by applying the 2-D DWT [10]. However, the method is short of classifying the disturbances.

A 2-D DWT decomposes a 2-D image into approximation and details which are related to the low and high frequency components of the image, respectively. Therefore, by omitting the approximation, and considering only the details, suitable features can be defined based on which various classes of disturbances can be distinguished from the regular sinusoidal signal. In this paper, a novel approach is proposed for the detection and classification of voltage disturbances based on the 2-D DWT and image processing techniques. The proposed approach can detect and classify a wide variety range of power quality disturbances, including steady state and low frequency disturbances such as harmonics, and high frequency disturbances such as oscillatory transients.

In this approach, a matrix is formed based on thirty two cycles of a given signal in such a way that each row of this matrix contains the samples of the voltage signal in one cycle based on the fundamental frequency of power system. This matrix can be regarded as a 2-D image. If there is no disturbance in the main signal, all cycles are almost the same, and all the rows almost look similar in the image, while the variations of samples in each row is with the main frequency. When the signal is disturbed, the pattern of the image will be different. A 2-D DWT in one level decomposes the main image into an approximation image which contains low frequency components of the main image in all directions and three detail images which mainly contain the high frequency components along the horizontal, vertical and diagonal directions. It can be said that variations in those directions are magnified in the corresponding images [3]. Now, new features can be defined to suitably characterize a wide variety range of power quality disturbances based on these images.

The methods presented in [17, 18], which are also based on 2-D DWT, are capable of detecting and classifying power quality disturbances, but the feature generation algorithm used, is based on statistical observations without any analytical base. In this paper, a novel feature generation algorithm is proposed based on image processing techniques, which results in more precise detection and classifying scheme.

Power quality disturbances are divided into seven categories based on IEEE 1159 standard [12]. Detecting some of these disturbances is simple. For example, detection of voltage imbalance is related to the magnitude of the three phase voltage and it can be easily detected after analyzing the three phases individually, or long duration variation disturbances can be determined by comparing voltage magnitude with its nominal amplitude in steady state. Therefore, the six following classes were considered for classification: ***Voltage sags, oscillatory transients, harmonics, interharmonics, notching and pure sinusoidal waveform***.

Designing a pattern recognition system for verifying and classifying various classes includes the steps shown in Fig. 1 [22]. For the task of classification of PQ disturbances, sensor is a digital data acquisition board used for sampling of voltage. A 2-D DWT is applied for feature generation, and the features are selected by a novel algorithm based on image processing techniques, in this paper. Performance of the system is evaluated by application of both One nearest neighbor and neural classifier systems based on a database of the six mentioned categories of disturbances, generated by simulation of a single phase 220 V, 50 Hz power system by MATLAB Simulink and MATLAB command line instructions in simpler cases based on the standard characteristics of the disturbances [12]. Fundamental frequency variations of 0.2 Hz are considered in the samples of the database.

2. TWO DIMENTIONAL REPRESENTATION OF POWER QUALITY DATA

A new approach for the analysis of power quality data is proposed in [11] which is the base of the analysis in this paper. In this approach, the samples of the voltage signal in each cycle form one row of a matrix which can be interpreted as a 2-D image. This procedure is illustrated in Fig. 2. The 2-D image for a pure sinusoidal signal is depicted in Fig. 3.

Due to the variations in power system fundamental frequency, exact calculation of the frequency and a variable sampling rate is necessary for precise selection of cycles, which is almost impossible in practice. In our analysis, cycles are selected based on the nominal power system frequency. Figs. 4a - 4d show the 2-D image for a pure sine wave and sinusoidal signals containing three different types of disturbances generated based on 32 cycles of the original signal. The fundamental frequency of signals is 49.9 Hz, but the samples are selected based on a period of 20 ms. The images are displayed in a grayscale format by normalizing the absolute value of each of them. In the grayscale representation of a normalized positive matrix, black represents zero and white represents one or the maximum of the matrix.

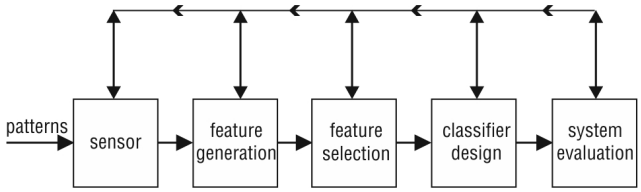

Fig. 1. Stages of designing a pattern recognition system [22]

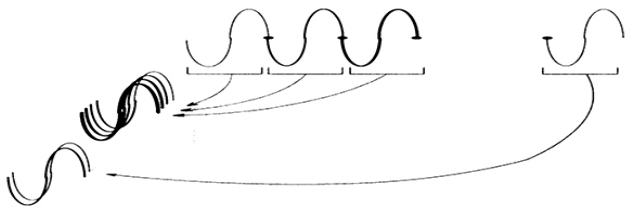

Fig. 2. Generation of a 2-D image or matrix from one dimensional signal [11]

Fig. 3. The 2-D image of a pure sinusoidal waveform with 32 cycles and the cycle length exactly equivalent to the period

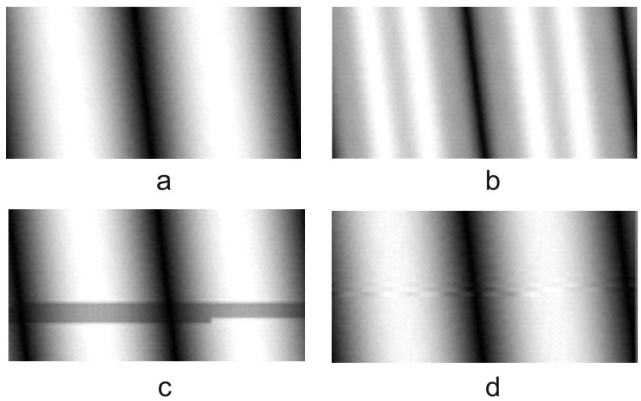

Fig. 4. The 2-D image for 32 cycles of (a) a pure sine wave voltage signal, (b) a harmonic polluted voltage signal, (c) a voltage signal containing a voltage sag, (d) a voltage signal containing an oscillatory transient with the fundamental frequency of 49.9 Hz and cycle length of 20 ms

3. THE TWO DIMENTIONAL WAVELET TRANSFORM

A 1-D DWT decomposes a 1-D signal to approximation and details which contain low and high frequency components of the signal, respectively. The frequency selection characteristics of the wavelet transform depend on the motherwavelet chosen [6, 19]. Biorthogonal 3.1 mother wavelet has shown to be suitable for characterization of power system transient disturbances and is used as the mother wavelet in this paper [2]. The implementation of 2-D DWT is similar to its 1-D counterpart, but it is implemented in two stages. First, each row of the matrix which represents a 2-D signal is decomposed into low and high frequency

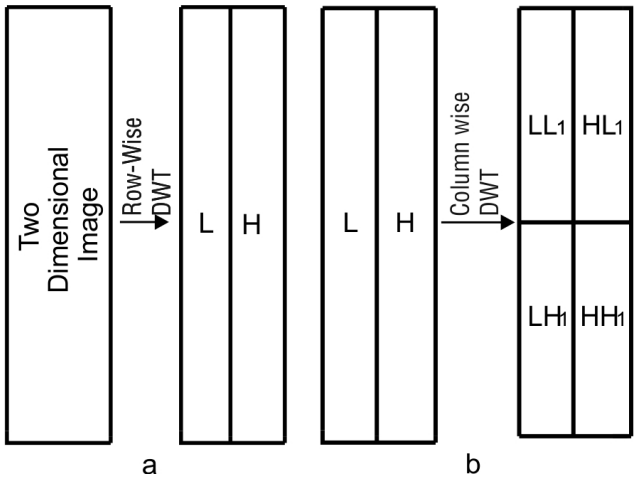

Fig. 5. (a) First stage and (b) Second stage of implementation of 2-D DWT [1]

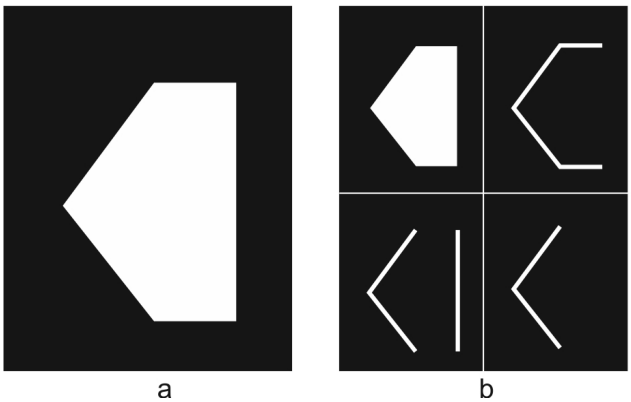

Fig. 6. (a) The original image and (b) its decomposition in one level using 2-D wavelet transform.

components by the 1-D DWT. This procedure is depicted in Fig. 5a. Then, each column of the resulting matrix is imposed to 1-D DWT, and each of the low and high frequency parts of the rows are decomposed into their low and high frequency parts along columns as shown in Fig. 5b.

It can be seen that the image is decomposed into four sub-images. The first one consists of the lowest frequency components along the rows and columns and is indicated in Fig. 5b as the LL1 image. This is the most similar image to the original image, but it does not contain the high frequency components. The second image indicated by HL1 contains the high frequency components along the rows and the low frequency components along the columns. The third image indicated by LH1 contains the low frequency components along the columns and the high frequency components along the rows. The fourth image indicated by HH1 contains the high frequency components along the rows and columns. Talking precisely, the variations of the main image along the horizontal, vertical and diagonal directions are magnified in HL1, LH1 and HH1 images, respectively [1, 3]. Fig. 6 shows the decomposition of a simple image into its approximation and details in one level.

4. TWO DIMENSIONAL PROCESSING OF POWER QUALITY DISTURBANCES

A 2-D DWT with its horizontal and vertical processing capability can be used to produce features which can suitably characterize various classes of power quality disturbances.

A feature generation method is proposed in [17] based on the fact that the approximation contains the lowest frequency components regarding the uniform and mono frequency sinusoidal nature of the voltage signal. In this approach, a 1-D signal is reconstructed from the details and the approximation is omitted, and by processing this signal, the features are defined for the detection and classification of the disturbances.

This approach, however useful, is only capable of classification of events and transients and does not result in good classification results for various classes of disturbances, and therefore, it is modified in [18] based on the fact that each of the details can be used to generate features for various classes of disturbances.

The method proposed in [18] is based on the fact that if we form a 2-D image as discused in part II, the vertical variations are the results of the variations of the voltage signal between different cycles, e.g. voltage sag, and the horizontal variations are the results of the variations of voltage signal which occur within the cycles periodically, such as notching. For example, consider the 2-D image generated for 32 cycles of a pure sinusoidal waveform with nominal amplitude sampled at 256 samples per cycle. The image will not contain any variations along the columns since the rows are almost the same, and along the rows, there will only be slow variations with the fundamental frequency as it can be seen in Fig. 4a. When the signal contains harmonics, in its 2-D image (Fig. 4b), there will be sharper changes along the rows, but there will be negligible changes along the columns since the rows are still almost the same. In Figs. 4c and 4d, which are the 2-D images generated for signals containing a voltage sag and a capacitor switching transient, an abrupt change could be seen along the columns. It can be concluded in general that steady state disturbances usualy contain higher frequencies along the rows and negligible changes along the columns as compared to the fundamental frequency. In contrast, transients and events of short duration variations create high frequency components along the columns. Therefore, events and transients can be characterized based on 'LH1' image, and steady state disturbances can be characterized based on 'HL1' image. 'HH1' image also helps us in disturbance charactarization, especially in the case of interharmonics which are steady state disturbances, but lead to the same pattern in more than one cycle.

Therefore, the four following images are created based on the details. The first image is created by taking an inverse 2-D DWT from the three detail images. The approximation image is set to zero for this first image. The resulting image contains all the details. The next three images are formed only based on one detail image and setting the other two detail images and the approximation image equal to zero and taking the inverse 2-D DWT. Each of these images contain variations along one of the horizontal, vertical or diagonal directions.

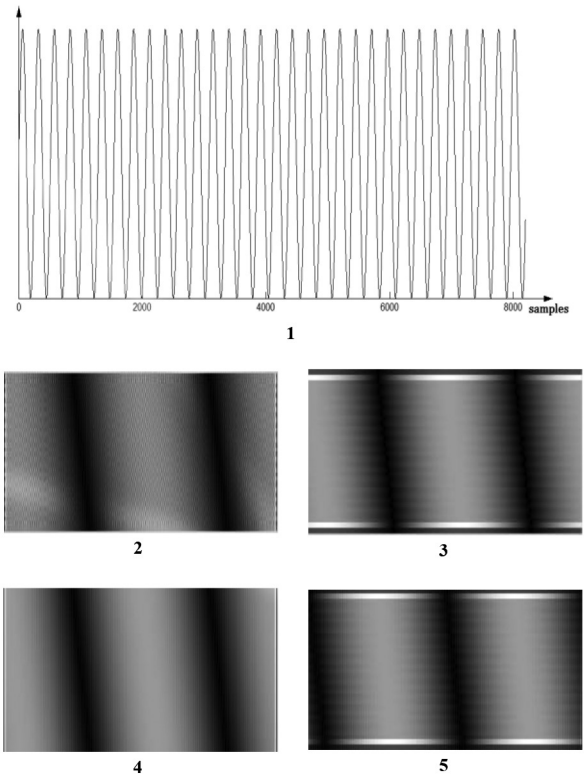

Fig. 7a. A pure sinusoidal waveform and the new resulted four images.

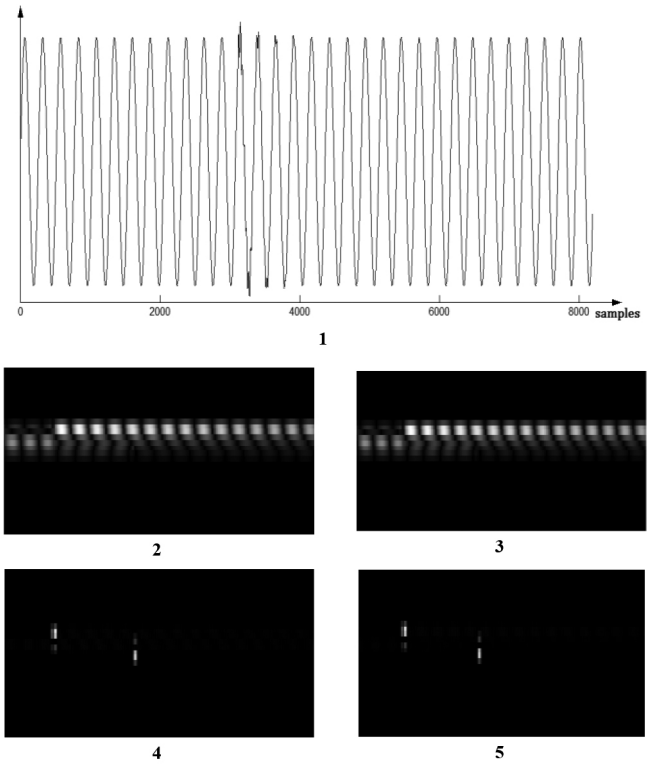

Fig. 7c. A sinusoidal waveform containing a capacitor switching transient and the new resulted four images.

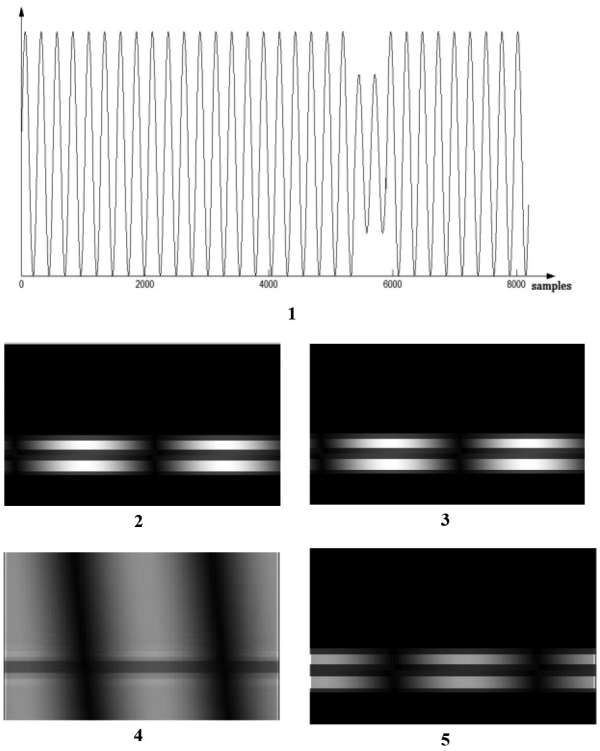

Fig. 7b. A sinusoidal waveform with a voltage sag and the new resulted four images.

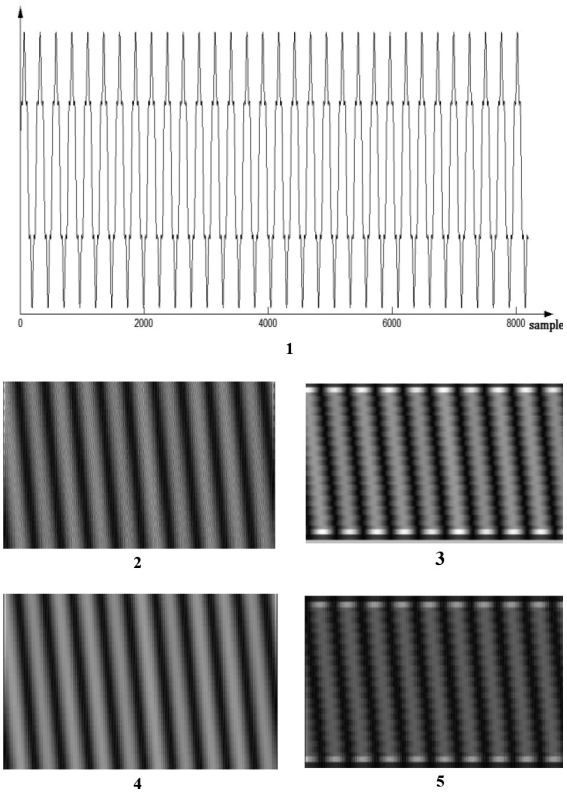

Fig. 7d. A sinusoidal waveform containing 20 percent of 5th harmonic and the new resulted four images.

Figs. 7a – 7f, show these four new images for a pure sinuoidal waveform and sinusoidal waveforms containing 5 types of power quality disturbances. Each of the 1-D signals contain 32 cycles of 256 samples. Therefore, the 2-D images contain 32 by 256 pixels along columns and rows respectively. The toppest row is related to the first cycle and

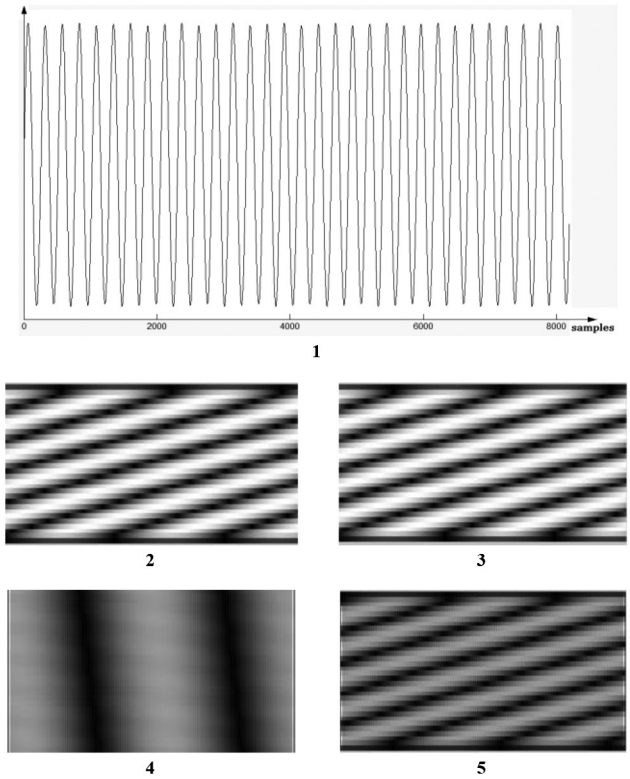

Fig. 7e. A sinusoidal waveform with one percent of 4/3th interharmonic component and the new resulted four images.

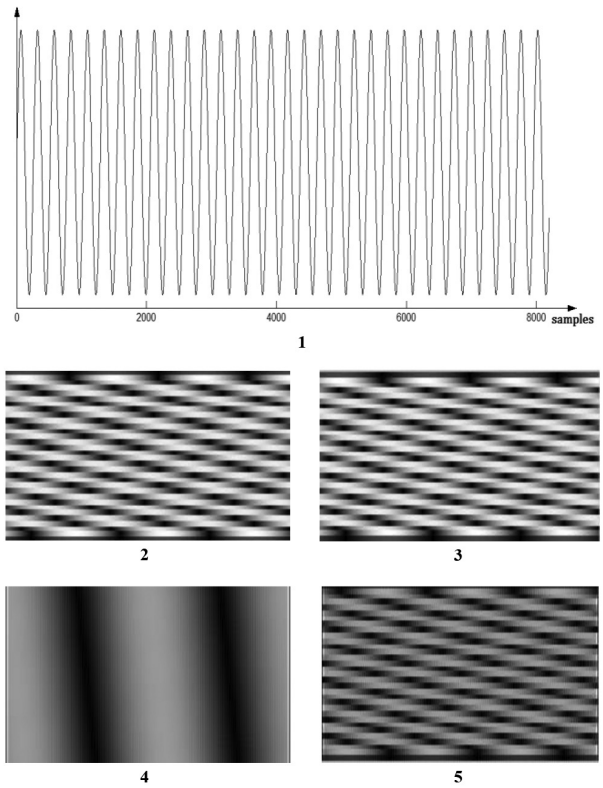

Fig. 7f. A sinusoidal waveform with 0.1 percent of 8/5 th interharmonic component and the new resulted four images.

the leftmost column is related to the first samples of each cycle. In all the figures and their transforms, image No.1 is the original 1-D waveform, image No.2 is obtained by taking the inverse 2-D DWT of the details with the approximation set equal to zero. Images 3, 4 and 5 are obtained in the same way by setting the aproximation and the details except one of the LH1, HL1, HH1 images equal to zero respectively, and taking the inverse 2-D DWT.

5. FEATURE GENERATION FOR POWER QUALITY DISTURBANCES

A good feature must contain the most amount of necessary information for classification and the least amount of redundant information. It can be seen from images shown in Fig. 7 that various types of disturbances create special patterns in the resulted four images and suitable features can be defined by processing them.

The four images are created based on the details of the 2-D DWT of the original 2-D image, omitting the low frequency components and magnifying the variations. In the grayscale representation of a normalized positive matrix, the illumination of each point is proportional to the magnitude of the matrix at that point and the whitest points correspond to the maximum values of the matrix. Therefore, it can be concluded that in the four images, the white patterns, correspond to the variations in the original 2-D image in horizontal, vertical or diagonal directions, which are magnified by 2-D DWT in each of the images. For example, the white patterns in the LH1 image of Fig. 7 (c) are corresponding to the oscillations caused by a capacitor switching in the original 1-D signal, and the white patterns in the LH1 image of Fig. 7 (b) are related to the start and end of the voltage sag in the main signal.

Therefore, features are defined based on the white patterns in each of the four new images. For this purpose, a point with amplitude of more than five percents of the maximum value is considered as a **white point** and a **white spot** is defined as set of continuous white points in each of the images. Talking precisely, the images are converted to the binary format by considering one for white points and zero for others, and sets of continuous white points are labeled as **white spots** based on a connected component labeling algorithm [15, 24].

Based on this fact, the following steps are used in order to generate proper features from the four images:

1. In order to omit the noise, an image with a maximum value of less than the maximum of the input 1-D signal divided by 10^6, is set equal to zero and all features regarding to such an image are considered as zero. In nonzero images, the first and the last two rows and columns are also set equal to zero, also.
2. For a nonzero image, sets of continuous white points are labeled as white spots and the following parameters are calculated for each of them: Maximum horizontal length, maximum vertical length, the average variance of the illumination of the points in the horizontal direction, the average variance of the illumination of the points in the vertical direction, the total illumination of each white

spot (sum of absolute value of elements of the white spot).

3. The following eight features are defined for each of the four images, and 32 features are defined for each voltage signal.
   - The total illumination of the image. (sum of the absolute value of the elements of the image)
   - The illumination of the most illuminated point. (maximum value of the image)
   - The number of white spots.
   - The mean value of the maximum horizontal length of the white spots.
   - The mean value of the maximum vertical length of white spots.
   - The mean of the average variance of the illumination of the points in the horizontal direction of the white spots.
   - The mean of the average variance of the illumination of the points in the vertical direction of the white spots.
   - The variance of the total illumination of the white spots.

6. CLASSIFICATION EXPERIMENTS

A classifier is a system that assigns an input feature vector to a specific class, based on special rules and mathematical manipulations. The parameters of such a system is determined in training process, based on a labeled training data set and its performance is evaluated in testing process, via a labeled test data set [8].

One nearest neighbor (1-NN) classifier system assigns an input vector to a class which has the nearest training sample to that input vector, as shown in Fig. 8. A neural classifier system classifies input vectors based on outputs of a neural network, which consists of units of neurons arranged in layers. Each unit takes an input and applies a function to it and then passes the output on to the next layer. At last, the input vector is mapped to some output based on which the classification is performed. The parameters of the network are determined in the training process. A two-layer feed-forward network, with 32 sigmoid neurons in hidden and 6 sigmoid neurons in the output layer, trained with scaled conjugate gradient backpropagation algorithm is applied in our classification tasks, as shown in Fig. 9 [5, 23].

The classification of the five classes of power quality disturbances defined in part 1 and a pure sinusoidal waveform, based on the 32 defined features is tested via a data set of 200 samples for each class. For this purpose, the data set is devided into 130 training samples and 70 test samples for each class, randomly.

The nearest neighbor and neural classifiers are trained based on the training data set by Matlab command line instructions and Matlab Neural Network Pattern Recognition Toolbox, respectively. At last, the test samples are applied to the classifier systems and all the test samples are classified correctly based on both the 1-NN and the neural classifier systems. The perfectness of results proves this method as an efficient feature generation algorithm for characterization of power quality disturbances.

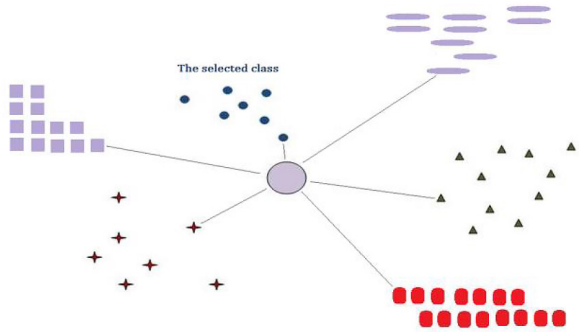

Fig. 8. Classification based on the nearest neighbor rule.

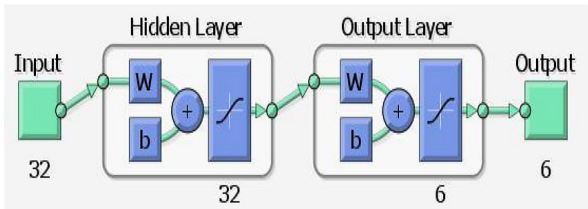

Fig. 9. A two-layer feed-forward network, with 32 neurons in hidden and 6 neurons in the output layer.

7. CONCLUSION

In this paper, 2-D analysis and characterization of power quality disturbances using image processing and pattern recognition techniques is introduced. A 2-D DWT is applied to the 2-D image obtained from a power system signal, and four images are generated based on the details of the 2-D DWT. Various disturbances create special patterns in these images. By processing the images, special features are extracted which can mathematically describe the disturbances. Using these features and classifier systems, a smart system is developed which can classify a wide variety of power quality disturbances.

The features are classified based on the nearest neighbor and neural classifier systems and the classification experiments prove the efficiency of the feature generation method and its robustness against frequency variations. Due to the vertical and horizontal processing capability of the 2-D-DWT, PQ events with slow waveform variations, even steady state disturbances, are possible to be detected and characterized at the beginning of their occurrence

With regard to the developments of computational tools, this algorithm can be implemented for online detection and characterization of power quality disturbances. This algorithm can also be used to detect and classify abnormal conditions of any periodic signal, with slow frequency variation, such as ECG signal, due to its vertical and horizontal processing.

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