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Detection and classification of power quality disturbances using parallel neural networks based on discrete wavelet transform

In this paper, a new method for the detection and classification of all types of power quality disturbances is presented. In addition to separating the disturbance signals, the proposed method is able to determine the type of disturbances. Disturbance waveforms are generated based on IEEE 1159 standard and they are de-noised using discrete wavelet transform. To detect the sinusoidal signals from disturbance signals, new criteria have been proposed. By introducing these new criteria, the classification algorithm is not active for non-disturbance signals. Therefore, the computation time is reduced. If a signal has disturbance, to extract the required information, it is analyzed using discrete wavelet transform. Using this information, the appropriate feature vectors are introduced. Parallel neural networks structures are proposed for the classification of disturbances. The inputs of these networks are the introduced feature vectors. The proposed method is done for all power quality disturbances including DC offset, flicker, interrupt, sag, swell, harmonic, notching, impulsive transient, oscillatory transient and eight combinations of these including the harmonics with transient, harmonic with flicker, harmonic with sag, harmonic with swell, sag with flicker, swell with flicker, transient with sag and transient with swell. The performance of this algorithm is compared with a single neural network structure. The results indicate using the parallel neural networks structure, computational time is much reduced and the accuracy of classification of power quality disturbances is significantly increased. Comparison the obtained results by the method with other methods, represents very high performance of the proposed method with precision %99.53.

Keywords: power quality disturbances; discrete wavelet transform; parallel neural networks; detection; classification; de-noising.

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1. Introduction

Power quality is service quality to customers and suppliers of electrical energy. It includes a wide range of the steady state phenomena to electromagnetic transient phenomena in distribution networks [1]. With the rapid development of various applications of sensitive and non-linear loads in distribution networks, power quality issues are becoming more important. The power quality is reduced by passing of non- sinusoidal current from the network. On the other hand, the effects of distortion and harmonics in voltage waveform on some loads are serious and the most sensitive loads need the sinusoidal voltage sources for proper performance. In order to improve the power quality, the detection and classification of power quality disturbances is essential.

In reported literatures, different ways based on short time Fourier transform (STFT), wavelet transform, S-transform, fuzzy logic, neural networks and genetic algorithms for the classification of power quality disturbances have been introduced. The best-known technique for frequency-domain analysis is the Fourier transform (FT). However, it just works well for the infinite time case of a stationary signal and it is unable to resolve any temporary information associated with fluctuations. To resolve this, the STFT divides the

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signal into small segments, where these signal segments can be assumed to be stationary [2]. The STFT works well provided that the window is short enough compared to the fluctuation rate. High rates of fluctuation can lead to significant errors [3].

Nowadays, WT is the most popular technique employed to obtain characteristic in time–frequency domain. Many kinds of mother wavelet have been proposed including complex wavelet [4]. Other works use the combination of WT and FFT for obtaining certain characteristics of the signal under analysis [5–8]. In [9], a method based on wavelet transform is presented to detect power quality disturbances. A combination of fuzzy logic and Fourier transform is suggested in [10]. In [11], a method based on neural-fuzzy is used for classification of disturbances. A combination of neural networks and genetic algorithms has been presented in [12]. In [13, 14], a technique based on fuzzy logic and wavelet transform is presented. In [15], a method based on S-transform and modular neural has been proposed. In [16], a new combination of S-transforms and neural network is introduced. In [17], a combination of the linear Kalman filter and fuzzy system has been used to classify of disturbances. In some of these references, the effect of noise is not considered. In some cases, classification accuracy is low. In some of them, a few of different types of disturbances have been studied.

In this paper, a new method based on the combination of discrete wavelet transform and parallel neural networks is presented. This method, in addition to have high classification accuracy, is able to classify a wide range of power quality disturbances and combinations of them. In this paper, the effect of noise is also considered.

2. Notation

The notation used throughout the paper is stated below.

Indexes:

t	time interval index

Constants:

$D(i)$	detail coefficients of the desired signal
N_d	the number of detail coefficients of the desired signal
$d(i)$	detail coefficients of a pure sinusoidal signal with the amplitude of 1 pu
$A(i)$	approximation coefficients of the desired signal
N_a	the number of approximation coefficients of the desired signal
$a(i)$	approximation coefficients of a pure sinusoidal signal with the amplitude of 1 pu
j	level of decomposition
c_N	approximation coefficients in level N
d_j	detail coefficients in level j
$\varphi(t)$	the scaling function
$\psi(t)$	the mother wavelet
N_{d_j}	the number of detail coefficients in level j
N_s	the number of samples of a signal
$\lvert S(i) \rvert$	signal value at i^{th} sample

3. The proposed method

A simplified flowchart of the proposed algorithm for the detection and classification of power quality disturbances is shown in Fig. 1.

This algorithm is based on the following steps:

- De-noising (to reconstruct a signal without noise, with the same energy content)
- Detection (diagnosis sinusoidal signals or disturbances)
- The feature vector (selection of suitable mother wavelet, obtain the wavelet coefficients at each level of decomposition and extract their useful information)
- Training of parallel neural networks (to the classification of power quality disturbances and their combinations)

3.1. De-noising

Noise in measurement systems reduces the accuracy of the classification of power quality disturbances. In this paper, to avoid the negative effect of noise and increasing the accuracy of the proposed method, all signals have been de-noised using wavelet transform. The reconstructed signal is free of noise and has the same energy content. Generally, the process of de-noising of signal using discrete wavelet transform is consists of three steps:

- Decomposition: decomposition of the signal to desired levels and calculating the wavelet coefficients at these levels.
- Thresholding: Selections of thresholding rules and reduce the amount of wavelet coefficients at desired levels, by comparing with the selected threshold value.
- Reconstruction: the process of inverse wavelet transform using the coefficients of the wavelet transform.

Thresholding is the most important part of de-noising using wavelet transform and it consists of two steps. The first step is the selection of thresholding rules and the second step is determining the threshold value. There are two types of thresholding rules:

- Hard thresholding: coefficients greater than the threshold value are retained and coefficients smaller than it setting to zero.
- Soft thresholding: coefficients lower than the threshold value will be zero and the remaining coefficients are equal to difference it with the threshold value.

In this paper, the soft thresholding has been used.

Proper selection of the threshold value has a significant impact on the quality of the process of de-noising the signal. The threshold value, with estimate the amplitude of the noise in the wavelet transform coefficients, is determined so as to minimize the possibility of noise. In this paper, a combination of Stein's unbiased risk estimate (SURE) method [18] and universal fixed thresholding method [19] has been used. This method is based on the idea that, when the signal to noise ratio is too small, output of SURE method will be associated by noise.

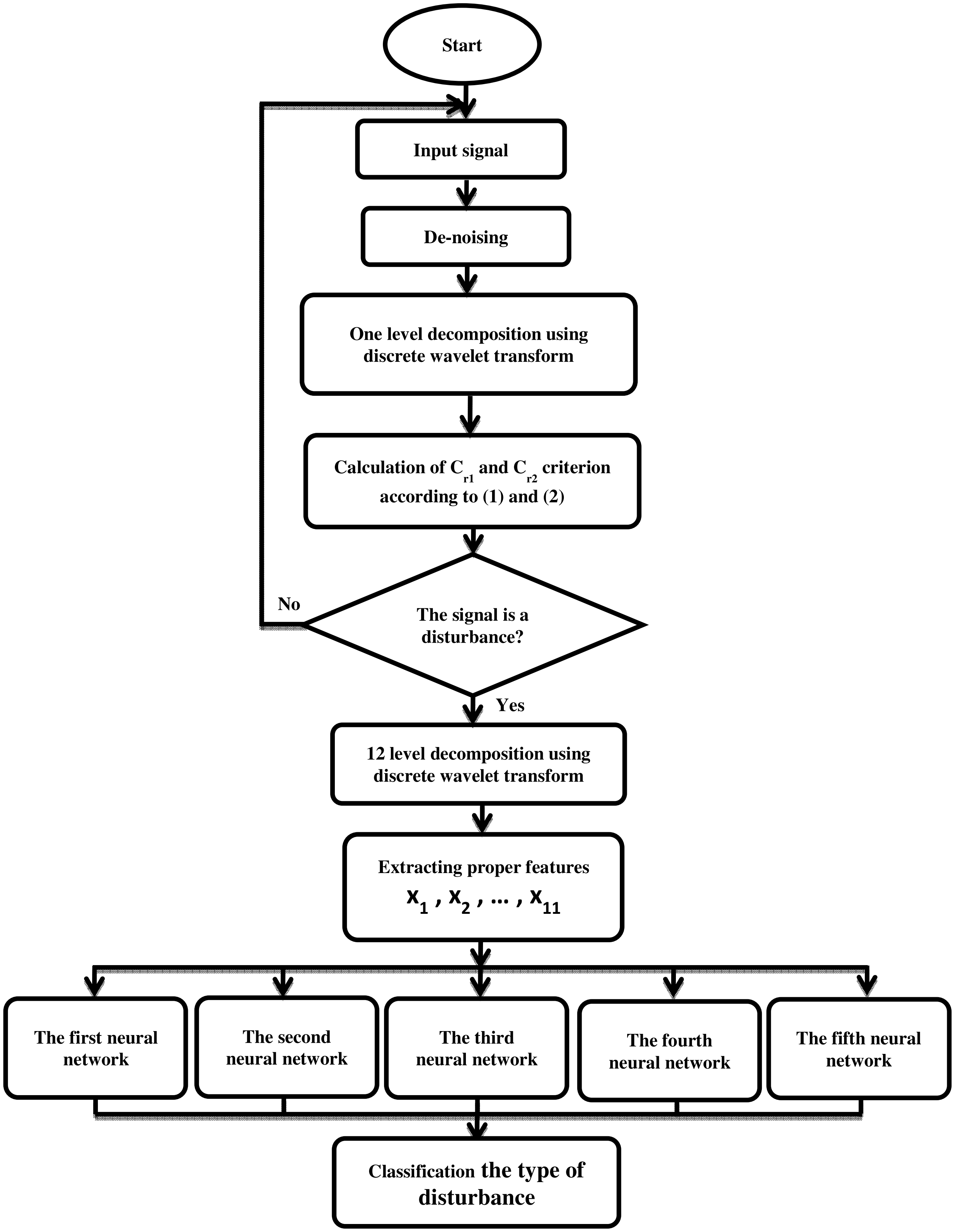

Figure 1: Flowchart of the proposed algorithm for classification of power quality disturbances using parallel neural networks

3.2. Detection of disturbances

In this paper, a new method for the detection of sinusoidal signals from disturbance signals is proposed. This method is based on the idea that after the signal is decomposed by discrete wavelet transform at one level, the detail coefficients of sinusoidal, flicker and DC offset signals are very smaller than the detail coefficients of other disturbances. On the other hand, the approximation coefficients of sinusoidal signals are much less than the approximation coefficients of DC offset and flicker. In this method, only wavelet transform decomposition of the signal at one level is required. After decomposition of the signal at one level, disturbances signal being detected from the relations (1) and (2).

$$C_{r1} = \frac{\sum_{i=1}^{N_d} |D(i)|^2}{\sum_{i=1}^{N_d} |d(i)|^2} \tag{1}$$

$$C_{r2} = \sum_{i=1}^{N_a} |A(i)|^2 - \sum_{i=1}^{N_a} |a(i)|^2 \tag{2}$$

In order to select the threshold value for c_{r1} and c_{r2} , 1700 signal is simulated in MATLAB and c_{r1} and c_{r2} value is calculated for each of them. With the comparison of c_{r1} and c_{r2} for various signals, it can be seen that if the threshold value for c_{r1} and c_{r2} are respectively selected 1000 and 10, the proposed method can detect sinusoidal signals from disturbance signals with 100% accuracy. If c_{r1} value for the input signal is greater than 1000, it is a disturbance signal. Otherwise, c_{r2} value will be calculated. If c_{r2} is less than 10, it is a sinusoidal signal and classification algorithm is not activated. Otherwise, it is a disturbance signal and the type of disturbance is determined by using the proposed algorithm.

In the most references, there is no such criterion and sinusoidal signal as well as other disturbances is detected after performing the classification algorithm. But, with a short calculation, sinusoidal or disturbance of the signal is determined, by these criterions.

3.3. Determination of the feature vector

In order to classification the disturbances, it is need to be extracted suitable features from the disturbed signal. Features should be chosen so that they can accurately classify and separate the disturbances. The features are extracted from properties of the disturbed signal and levels of its decomposition. A set of the selected features forms a feature vector.

For example, Figs. 2 to 6 show voltage sag, interrupt, flicker, harmonic, transient, their approximation and their detail coefficients at levels 1, 2, 3 and 4 using rbio 3.1.

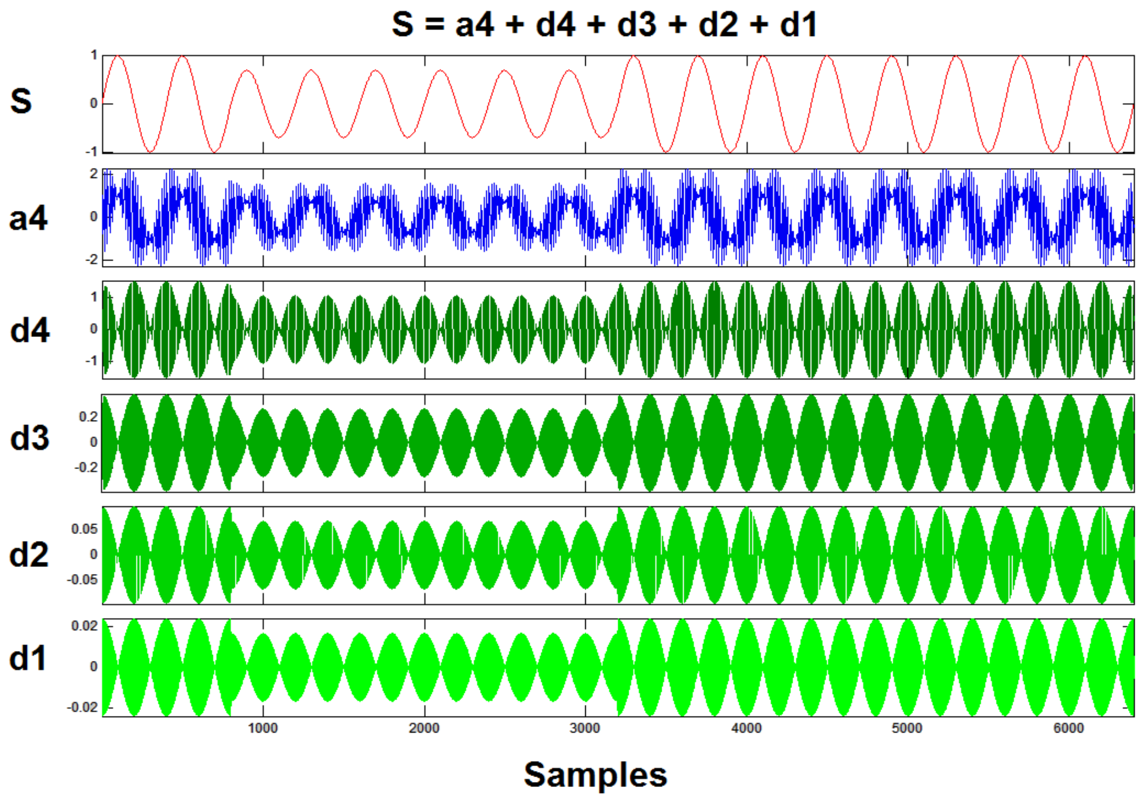

Figure 2: voltage sag, its approximation and its detail coefficients at levels 1, 2, 3 and 4

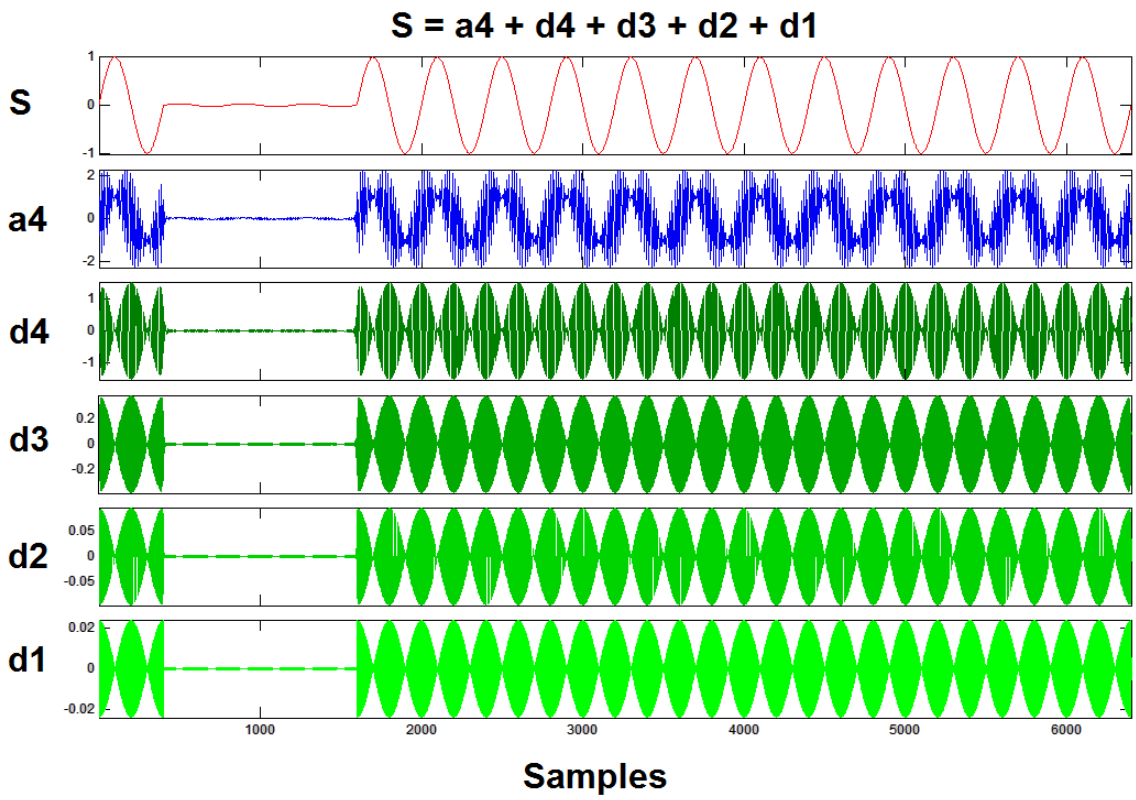

Figure 3: interruption, its approximation and its detail coefficients at levels 1, 2, 3 and 4

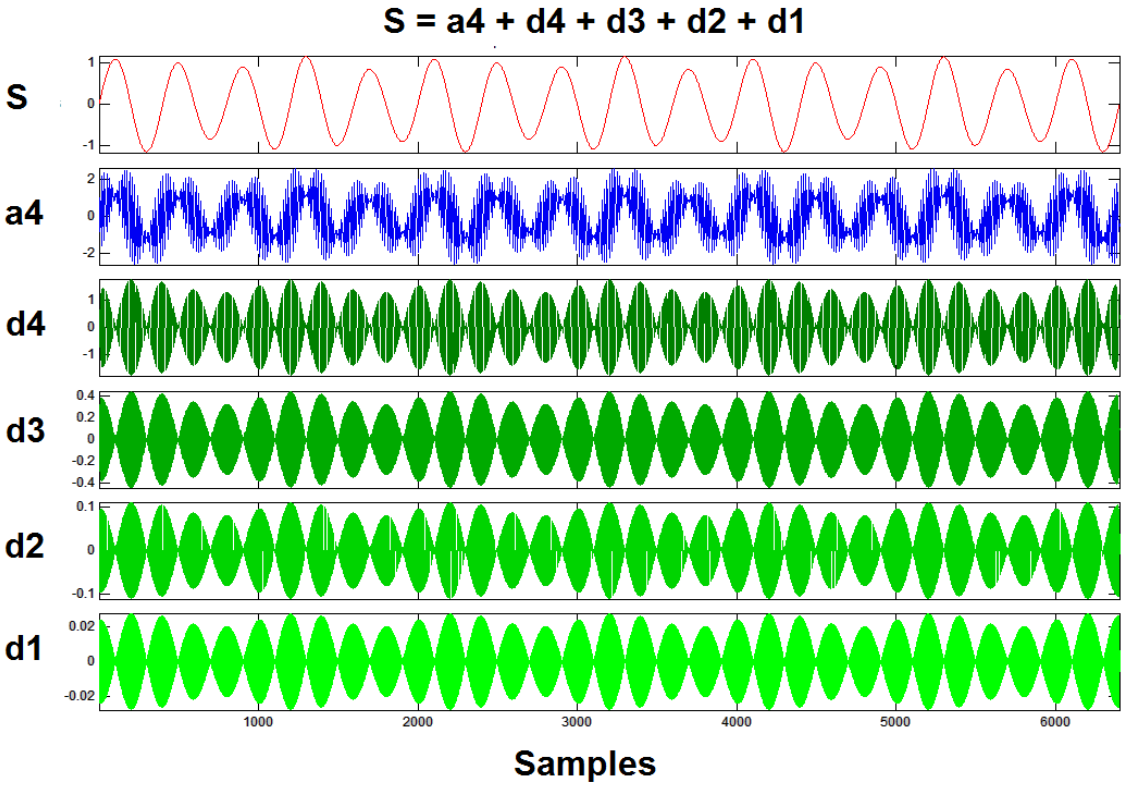

Figure 4: flicker, its approximation and its detail coefficients at levels 1, 2, 3 and 4

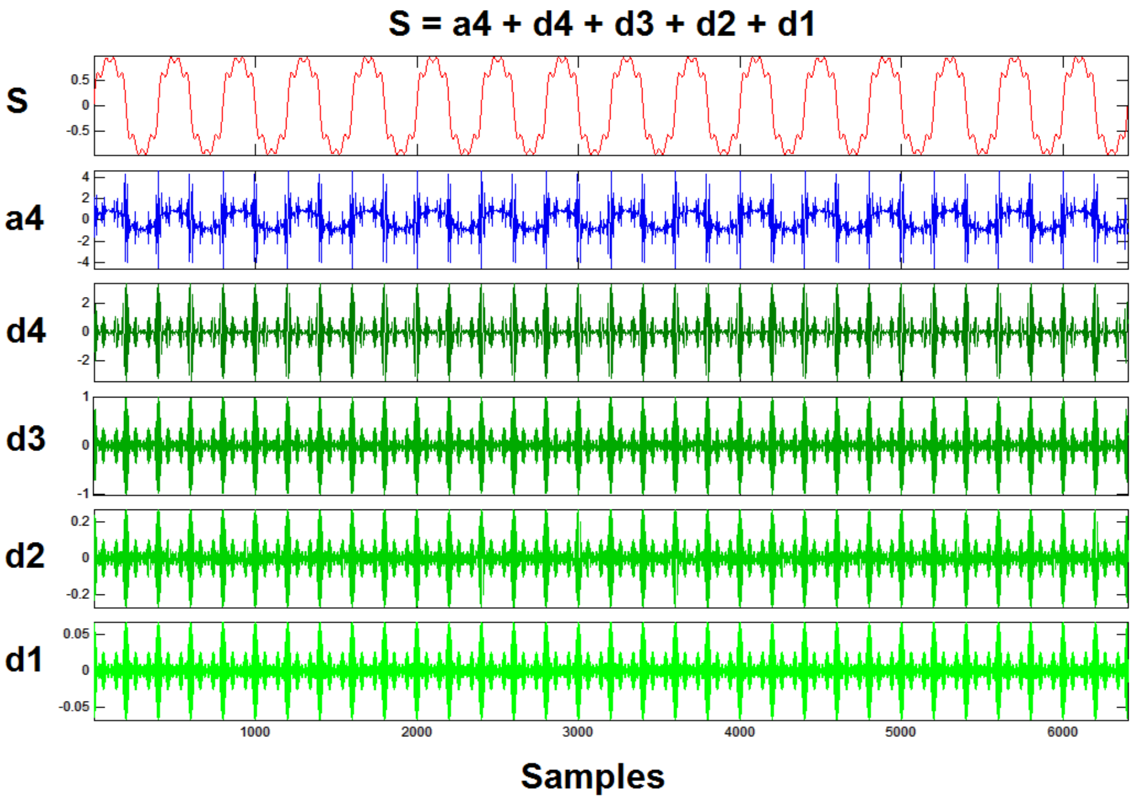

Figure 5: harmonic, its approximation and its detail coefficients at levels 1, 2, 3 and 4

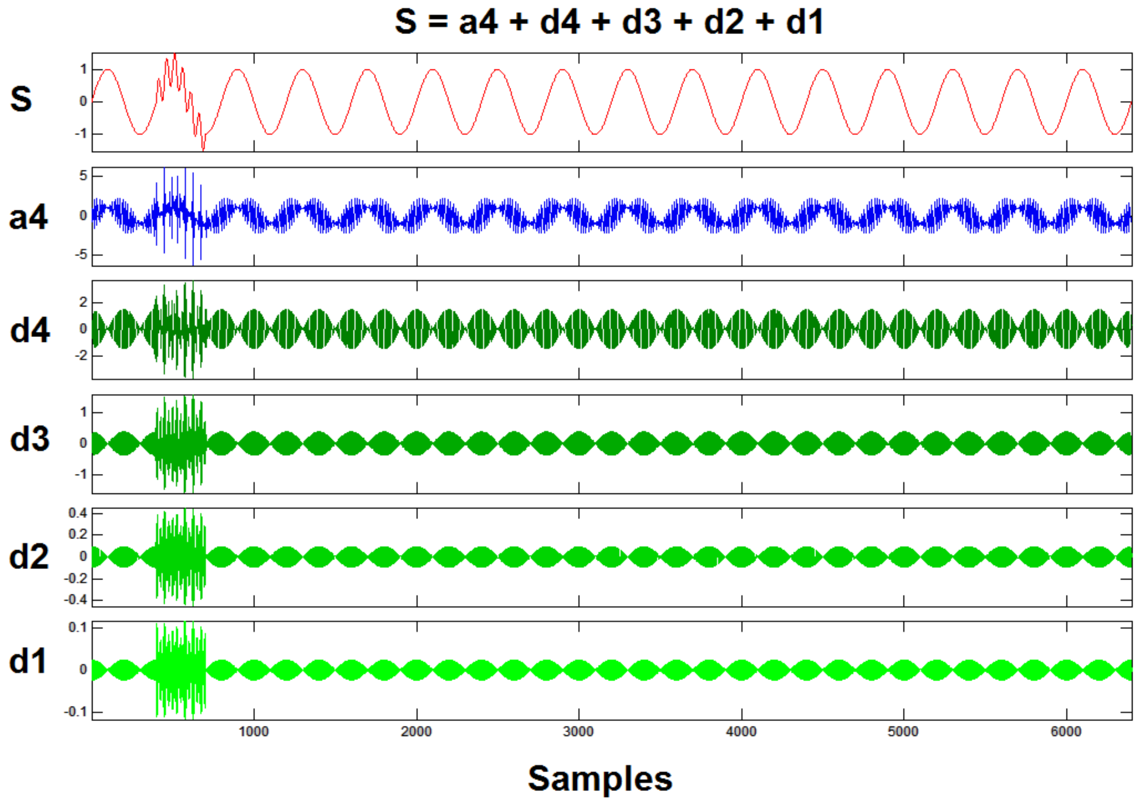

Figure 6: transitent, its approximation and its detail coefficients at levels 1, 2, 3 and 4

3.3.1. Selection of suitable mother wavelet

To determine a suitable mother wavelet, 57 mother wavelets in MATLAB software toolbox have been simulated. In each simulation, the signal is decomposed to 12 levels. Then the feature vector is considered as neural network input. The final results of the simulations are presented in Table 1. According to the table, the wavelet rbio3.1 has better performance for separation disturbances than other wavelets. So, to extract feature vector, this mother wavelet is used for decomposing of the signal, in this paper.

3.3.2. Feature extraction

After studying the results of the simulation using different parameters, the following parameters are selected as appropriate features to form a feature vector.

$$x_1 = \frac{Std\_absS_{d_{1,2,3}}(t)}{Mean\_absS_{d_{1,2,3}}(t)} \tag{3}$$

$$x_2 = \frac{Std\_absS_{d_{4,5,6}}(t)}{Mean\_absS_{d_{4,5,6}}(t)} \tag{4}$$

Table 1: The classification percent of the proposed method with 57 different mother wavelets

Mother wavelet used	Percentage of correct classification	Mother wavelet used	Percentage of correct classification	Mother wavelet used	Percentage of correct classification
Haar	97.28	Sym4	93.74	Bior3.9	95.41
Db2	96.79	Sym5	97.03	Bior4.4	91.65
Db3	94.84	Sym6	90.63	Bior5.5	92.33
Db4	95.52	Sym7	94.46	Bior6.8	90.44
Db5	96.54	Sym8	92.71	rbio1.1	96.37
Db6	95.59	Sym9	97.15	rbio 1.3	96.42
Db7	91.29	Sym10	93.21	rbio 1.5	96.56
Db8	96.78	Sym11	95.86	rbio 2.2	95.93
Db9	94.50	Bior1.1	98.51	rbio 2.4	96.24
Db10	95.24	Bior1.3	95.75	rbio 2.6	95.47
Db11	94.64	Bior1.5	95.24	rbio 2.8	94.79
Coif1	90.32	Bior2.2	89.71	rbio 3.1	99.53
Coif2	89.91	Bior2.4	90.12	rbio 3.3	96.87
Coif3	88.85	Bior2.6	91.57	rbio 3.5	97.17
Coif4	90.55	Bior2.8	89.90	rbio 3.7	99.34
Coif5	91.44	Bior3.1	89.66	rbio 3.9	97.87
Dmey	90.93	Bior3.3	91.45	rbio 4.4	95.04
Sym2	96.95	Bior3.5	94.43	rbio 5.5	93.06
Sym3	94.24	Bior3.7	97.14	rbio 6.8	94.97

$$x_3 = \frac{Std\_absS_{d_{7,8}}(t)}{Mean\_absS_{d_{7,8}}(t)} \tag{5}$$

$$x_4 = \frac{Std\_absS_{d_{9,10,11,12}}(t)}{Mean\_absS_{d_{9,10,11,12}}(t)} \tag{6}$$

$$x_5 = Max\_absS_{d_2}(t) \tag{7}$$

$$x_6 = Max\_absS_{d_5}(t) \tag{8}$$

$$x_7 = Max\_absS_{d_8}(t) \tag{9}$$

$$x_8 = Max\_absS_{c_{12}}(t) \tag{10}$$

$$x_9 = E_{d_1} \tag{11}$$

$$x_{10} = E_{c12} \tag{12}$$

$$x_{11} = \sqrt{\frac{\sum_i |S(i)|^2}{N_s}} \tag{13}$$

Calculation of above parameters is described as fallows.

Assuming arbitrary signal $S(t)$ is decomposed into N levels using discrete wavelet transform according to the equations (14).

$$S(t) = S_{c_N}(t) + S_{d_1}(t) + \ldots + S_{d_N}(t) \tag{14}$$

The input signal $S(t)$ can be divided into two sub-signals $S_{c_N}(t)$ and $S_{d_j}(t)$ as fallows.

$$S_{c_N}(t) = \sum_i c_N(i)\varphi(t-i) \tag{15}$$

$$S_{d_j}(t) = \sum_i d_j(i) 2^{j/2} \psi(2^j t - i) \tag{17}$$

The calculated mean value of the detail coefficients of the signal $S(t)$ in level j of decomposition can be obtained from equation (17).

$$Mean\_absS_{d_j}(t) = \frac{1}{2^j N_{d_j}} \sum_i |d_j(i)| \tag{17}$$

The standard deviation of absolute values of detail coefficients at level j is obtained from the relationship (18).

$$Std\_absS_{d_j}(t) = \sqrt{\frac{1}{2^j N_{d_j}} \sum_i (|d_j(i)| - Mean\_absS_{d_j}(t))^2} \tag{18}$$

Parameters (3) to (10) have been proposed in reference [13]. In this paper, to classify the disturbances with higher accuracy, in addition to these parameters, the other three parameters (equations (11) to (13)) also have been added to the feature vector. The reasons for choosing these three features are described as fallows.

The disturbance signal energy is one of the best features that can be used as a parameter of the feature vector. Because, the energy content of the kinds of disturbances is different and this feature takes different values in the most disturbances signals and makes distinguish between the feature vectors of different disturbances.

Assuming that the signal $S(t)$ is decomposed in N level using wavelet transform, energy of the signal $S(t)$ is calculated as fallows.

$$E = \sum |s(t)|^2 = \sum_i |c_N(i)|^2 + \sum_{j=1}^{N} \sum_i |d_j(i)|^2 \tag{19}$$

Where $\sum |s(t)|^2$ represents the total energy of the signal, $\sum_i |c_N(i)|^2$ is the energy of the approximate level and $\sum_{j=1}^{N} \sum_i |d_j(i)|^2$ indicates the total energy of the details levels from level 1 to N.

Relation (19) shows that energy of each signal in wavelet transform is obtained from total of energy of different levels of wavelet transform. The energy of j level of detail and the energy the approximate level are calculated according to the relations (20) and (21).

$$E_{d_j} = \sum_i |d_j(i)|^2 \tag{20}$$

$$E_{c_N} = \sum_i |c_N(i)|^2 \tag{21}$$

From the values obtained from energy of details levels and approximation level, energy of the first level of details and energy of the approximation level have been selected as two features of the feature vector (x_9, x_{10}).

When there is a transient phenomenon, the most important characteristic that will change is effective amount of voltage. Therefore, in this paper, effective value of voltage as an auxiliary characteristic along with other characteristics of the feature vector is used to classify the disturbances. The effective voltage can be calculated from the relationship (13).

3.4. Parallel neural networks

In this paper, five parallel neural networks are used for classification of power quality disturbances. By this way, the studied disturbances are classified according to duration of the disturbance. For classification of each category, one neural network is used. These networks are a perceptron network with one hidden layer. Inputs of each of these networks are defined according to the equations (3) to (13).

The first neural network is used to classify short-term disturbances include sag, swell and interrupt. The number of hidden layer neurons is selected equal to 22. With this number of neurons, the disturbances are classified with 99.33% accuracy. The second neural network classifies impulsive transient and oscillatory transient. The results show when the network has 20 neurons in the hidden layer, it classifies transient disturbances with 100% accuracy. Third neural network is used to classify steady state disturbances such as harmonic, DC offset, flicker and notching. The number of hidden layer neurons is selected equal to 11. With this number of neurons, the accuracy of classification disturbances is 100%.

The fourth neural network is applied to classify four combination disturbances include harmonic with sag, harmonic with swell, sag with flicker and swell with flicker. With 23 neurons in the hidden layer, it classifies these disturbances with 99% accuracy. The fifth neural network used to classify other studied combination disturbances consist of transient with sag, transient with swell, harmonic with transient and harmonic with flicker. The number of hidden layer neurons is selected equal to 11. In this case, the disturbances are classified with 99.50% accuracy.

The numbers of neurons in each of above neural networks has been obtained by using the results of training and testing the neural network (with different number of neurons).

Training of these neural networks is off-line. For This purpose, large number waveforms is required. In this paper, the required disturbance waveforms are simulated in MATLAB. Sampling frequency of these waveforms is 20 kHz and power frequency is 50Hz. Waveforms are consisted of 16 cycles of signal samples (in pu). For each type disturbance, 100 waveforms are simulated (total number of 1700 signal), that these are different in amplitude and duration of disturbance. For closer the simulated waveforms to the actual waveforms, white noise are added to them. The feature vector is obtained by using of rbio3.1 wavelet and the relations (3) to (13). For each of the five parallel neural networks, these 1700 feature vectors are used as training and test data. Percentage of correct classification of disturbances using the five parallel neural networks for all kinds of studied disturbances is according to the third column of Table 2.

Table 2: Percentage of correct classification of disturbances with a single neural network and with the five parallel neural networks

Type of power quality disturbances		Percentage of correct classification of algorithm using a single neural network	Percentage of correct classification of algorithm using the five parallel neural networks
1	sag	100	100
2	swell	99	99
3	interrupt	100	99
4	harmonic	100	100
5	flicker	100	100
6	notching	99	100
7	impulsive transient	97	100
8	oscillatory transient	98	100
9	DC offset	100	100
10	sag + harmonic	100	100
11	swell + harmonic	100	99
12	flicker + harmonic	100	100
13	harmonic + transient	99	100
14	sag + transient	99	98
15	swell + transient	98	100
16	sag + flicker	98	99
17	swell + flicker	97	98
	sum	99.06	99.53

4. Comparison of the five parallel neural networks with one single neural network

The results of parallel neural networks algorithm have been compared with the results of one single neural network.

4.1. A single neural network

In this paper, many studies were performed on different structures of the neural network and the results indicate that the best possible design for one single neural network is perceptron network with two hidden layer. The number of neurons in the hidden layer of this network based on the results of training and testing the neural network (about 200 different cases) is selected 72 neurons. Feature vector used for this network is same the feature vector in parallel structure. Also, the number of neurons in the output layer is considered equal to the number of disturbances (equal to 17). Percentage of correct classification of disturbances using a neural network for different types of studied disturbances is according to the second column of Table 2.

4.2. Advantages of the five parallel neural networks

More simplify the classifier structure, improving of results and reduce training time and recall time of the network are among the benefits of replacing a single neural network with the five parallel neural networks.

Implement of the five parallel neural networks with one hidden layer for each the network and with low neurons is simpler than implement a single neural network with two hidden layers and with higher neurons in each layers.

Table (2) shows percentage of correct classification of all disturbances using one single neural network and using the five parallel neural networks. This table shows that classification percent by using the five parallel neural networks has improved from 99.06% to 99.53%.

Recall time for both structures is provided in table (3). This table shows that the recall time using the five parallel neural networks is reduced about to a third recall time with a neural network. Simulations are done in the system with core i3 processor and the speed of 2.26 GHz and 4.00 GB of RAM.

Table 3: Comparison between recall times a single neural network with the five parallel neural networks

classifier structure	five parallel neural networks	a single neural network
recall time (seconds)	0.007353	0.022329

5. Effect of noise

The effect of noise on the performance of the proposed method is shown in table (4). According the table, the proposed method in different levels of signal to noise ratio (SNR), has excellent performance and this is because the use of proper de-noising method.

Table 4: evaluating the performance of the proposed method for signals with different SNR

signal to noise ratio (db)	20	30	35	40	50
Percentage of correct classification	98.76	98.99	99.19	99.53	99.57

6. Comparison of the proposed method with other methods

The proposed method results in classification of disturbances are compared with some other methods. The results are presented in Table 5. In [15, 21, 22, 23], the effects of noise have not been considered. In [17], in signal-to-noise ratio of 20 db, classification accuracy is low. The proposed method in different levels of SNR classifies the disturbances with high precision.

Table 5: Comparison of the classification accuracy of the proposed method with other references in terms of percentage

	Power quality disturbances	References							
		Self-Organizing Learning Array System [23]	S-transform and modular NN [15]	Fuzzy C-Means and APSO [21]	Dynamic Time Warping Classifier [22]	Kalman filter and fuzzy-expert system [17]		The method proposed in this paper	
		50 db noise	No noise	No noise	No noise	20 db noise	40 db noise	20 db noise	40 db noise
1	sinusoidal	100	100	-	100	-	-	100	100
2	sag	87	98	-	97	93	100	98	100
3	swell	100	92	100	98	94	100	96	99
4	interrupt	80.50	100	-	-	92	100	99	99
5	harmonic	100	92	100	100	90	97	99	100
6	flicker	-	98	94	89	-	-	100	100
7	notching	-	97	90	-	-	-	97	100
8	impulsive transient	-	90	100	-	92	98	98	100
9	oscillatory transient	-	100	97	100	-	-	100	100
10	DC offset	-	-	-	-	-	-	100	100
11	sag + harmonic	97	93	88	-	93	98	99	100
12	swell + harmonic	100	90	99	-	92	98	98	99
13	flicker + harmonic	-	-	99	-	-	-	100	100
14	harmonic + transient	-	-	-	-	-	-	99	100
15	sag + transient	-	-	-	-	-	-	98	98
16	swell + transient	-	-	-	-	-	-	100	100
17	sag + flicker	-	-	-	-	-	-	99	99
18	swell + flicker	-	-	-	-	-	-	99	98
	sum	94.93	95.45	96.33	97.33	92.29	98.71	98.83	99.56

7. Conclusion

In this paper, a new method based on discrete wavelet transform and parallel neural networks is proposed for detection and classification of power quality disturbances. This method is able to classify a wide range of disturbances, including DC offset, flicker, interrupt, sag, swell, harmonic, notching, impulsive transient, oscillatory transient and eight combination disturbances with very high accuracy. In this method, the new identification criteria are used for detecting non disturbance signals and preventing additional computation. Comparison of the results of the parallel neural networks with a single neural network shows that the accuracy of classification of power quality disturbance using parallel neural networks is very better than a single neural network. Evaluating of the proposed algorithm in different SNRs indicates that the algorithm can classify disturbances with very high accuracy in all SNRs. the classifier structure in the parallel neural networks is relatively simple. Therefore computational time is reduced. The results show superiority of the proposed method with other methods.

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