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Research Article

Classification of Single and Combined Power Quality Disturbances Using Stockwell Transform, Relieff Feature Selection Method and Multilayer Perceptron Algorithm

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ABSTRACT: In this study, a method based on Stockwell transform (ST), ReliefF feature selection method and Multilayer Perceptron Algorithm (MPA) algorithm was developed for classification of Power Quality (PQ) disturbance signals. First of all, ST was applied to different PQ signals to obtain classification features in the method. Then, total of 30 different classification features were obtained by taking different entropy values of the matrix obtained after ST and different entropy values of the PQ signals. The use of all of the classification features obtained causes the method to be complicated and the training/testing times to be prolonged. Therefore, so as to determine the effective ones among the classification features and to ensure high classification success with less classification features, ReliefF feature selection method was used in this study. PQ disturbances were classified by using 8 different classification features determined by ReliefF feature selection method and MPA. The simulation results show that the method provides a high classification success in a shorter training/testing time. At the same time, simulation results have shown that the method was successful on testing data with noise levels of 35 dB and above after only one training.

Keywords: Classification, Multilayer perceptron algorithm, Power quality, Relief feature selection, S-transform.

1. INTRODUCTION

In some cases, different faults can occur in power systems due to technical or environmental factors. It is necessary that these signals must be continuously monitored and classified in order to respond more effectively and faster to faults that may occur in power systems. When the methods used in these studies were examined, it is seen that firstly, classification features were obtained with a certain signal processing method, and then Power Quality (PQ) disturbances were classified using these classification features and a classification algorithm [1-4]. Many different signal processing tools such as Discrete Wavelet transform [5-8], Wavelet packet transform [9,10], Gabor–Wigner transform [11], Hilbert–Huang transform [12], Variational Mode decomposition [13] and Stockwell transform (ST) [14-19] were used to analyze PQ disturbances. After obtaining the classification features, different classification algorithms such as neural networks [5,14,15], probabilistic neural network [12,19], modular neural network

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[16], support vector machines [6,10], fuzzy logic [7], fuzzy expert system [17], fuzzy k-nearest neighbor [9] and decision tree [13] were used to classify PQ disturbances.

In addition to these, in some studies, different feature selection methods were also used for classification. The main purpose of feature selection methods is to determine the effective ones among the classification features. In this way, it is aimed to get high classification success with fewer features. Artificial bee colony feature selection method [8], genetic algorithm [9], particle swarm optimization [17] and statistical approach [19] were used as a feature selection method. Detailed analyzes of the methods used in the analysis of PQ signals can be found in [1-4].

ST signal processing method was used in many studies in view of the fact that it can examine PQ signals in both the time and frequency domains [14-19]. Also, different neural network structures were used in many different studies because of their being effective for classification [5,12,14-16]. Therefore, ST was used as signal processing method, while Multilayer Perceptron Algorithm (MPA) was used as classification algorithm in this study. At the same time, ReliefF feature selection method was used to determine effective classification features in this study.

In the literature, Relief feature selection method with DWT/ Hyperbolic S-transform [20] and ReliefF feature selection method with Fourier transform were used [21]. Differently, in this study, ReliefF feature selection method with ST-MPA were used.

The simulation results showed that the proposed method was successful. At the same time, simulation results show that the proposed method can classify PQ disturbances at different noise levels with high accuracy after only one training.

2. STOCWELL TRANSFORM (ST)

ST is an effective signal processing tool that enables the analysis of signals in the time-frequency domain.

For a continuous-time signal, its ST is given as in Eq.(1) [22].

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-j2\pi f t} dt \tag{1}$$

The discrete Fourier transform of continuous time *h(t)* is given by Eq.(2).

$$H\left[\frac{n}{NT}\right] = \frac{1}{N} \sum_{k=1}^{N-1} h(kt) . e^{j2\pi nk} \tag{2}$$

In this Eq.(2), n takes $n = 0, 1, \ldots N-1$ values. By replace n/NT for f and lT for τ in Eq. (1), the generalized S-transform is obtained as in Eq. (3). In Eq. (3), the Gaussian function is represented as in Eq.(4), with l, m and $n = 0, 1, \ldots, N-1$ [22].

$$S\left[lT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} \mathbf{H}\left[\frac{m+n}{NT}\right] G(m, n) e^{j2\pi ml/N} \tag{3}$$

$$G(m, n) = e^{-2\pi^2 m^2 \alpha^2 / n^2} \tag{4}$$

Two-dimensional TF Time-Frequency contour is obtained with the S-transform of the signal in Eq.(3). The output of S-transform is an $N\times M$ matrix called S-matrix whose rows pertain to frequency and columns to time.

3. RELIEFF FEATURE SELECTION METHOD

The logic of the method is similar to neighborhood algorithms. Also, it works by weighting the closest samples in the classes to which the sample with the feature belongs or not. The general ReliefF algorithm is shown in Figure 1 [23,24].

1. initialize vector **W**

2.for $i=1$ **to** m **do**

3. randomly select an instance R_i

4. find k nearest hits H_j

5. for all classes $C \neq cl(R_i)$ do

6. from class C find k nearest misses M_j(C)

7. **end for**

8. **end for**

9. **for** A=1 **to** a **do**

10. $AH = -\sum_{j=1}^{k} diff \frac{A,R_i H_j}{m.k}$

11. $AM = \sum_{C\neq cl(R_i)} \left[\left(\frac{P(C)}{1-P(cl(R_i))} \right) \sum_{j=1}^{k} diff\left(A, R_i, M_j(C)\right) \right] / (m.k)$

12. $W[A] = W[A] + (AH + AM)$

13. **end for**

14. **end for**

Figure 1. Pseudo code of ReliefF feature selection algorithm

As seen here, m is the number of iteration. At the same time, m corresponds to the number of samples from data to perform the estimation. Each selected sample R_i equally contributes to the a-size weights vector W. The number of features in the dataset is indicated by a. The algorithm by random selection picks an instance R_i then it searches for k nearest neighbours from the same class (H_j). The algorithm also searches for k nearest neighbours from each of class (nearest misses M_j(C)). The algorithm updates the vector *W[A]* of estimations of the qualities of attributes depending on R_i, H_j, and M_j(C). The whole process is repeated m times. A detailed explanation of the method can be found in [23,24].

4. MULTILAYER PERCEPTRON ALGORITHM

The MPA is basically a neural network-based artificial intelligence algorithm. This algorithm consists of the input layer, hidden layers, and output layer. One or more hidden layers can be used according to the methods [25,26].

Eq.(5) and Eq.(6) show the connection between input and output functions.

$$T = \sum_{i=1}^{n} x_i w_i + w_0 \tag{5}$$

$$Y=f(T) \tag{6}$$

As can be seen from the Eq.(5) and Eq.(6), the inputs are multiplied by weights and then summed up with a threshold. Finally, an activation function is used to calculate the output. Sigmoid activation function is shown Eq.(7) [25,26].

$$sigmoid(x) = \frac{1}{1+e^{-x}} \tag{7}$$

5. SIMULATION RESULTS

In this study, sine, sag, swell, harmonic, transient, interruption, sag with harmonic, swell with harmonic and flicker signals were investigated. The above-mentioned signals were produced synthetically and the parameters of the signals were randomly selected within the ranges specified in [27]. The sampling frequency of the signals was chosen as 3.2 kHz.

The MATLAB program was used for the signal generation and feature extraction. The WEKA program was used for the ReliefF and MPA algorithms.

WEKA program is a currently-used program in data mining and different PQ studies [28,29]. The sigmoid activation function was used in the MPA algorithm in WEKA and the number of neurons was determined automatically. While 19 neurons were determined for 30 classification features, 8 neurons were determined for 8 classification features. The network structure was single layer and backpropagation method was used. The general steps of the classification method used in the study are shown in Figure 2.

So as to test the success of the method, training and testing data were generated under different conditions.100 different simulations were performed for each PQ disturbance in the training data. In total, 900 different faults occurred for 9 different PQ disturbances.40 dB noise was added to the generated training data.

Similarly, 100 different simulations were performed for each PQ event in the testing data. In total, 900 different faults occurred for 9 different PQ disturbances. 40 dB noise was added to the generated testing data.

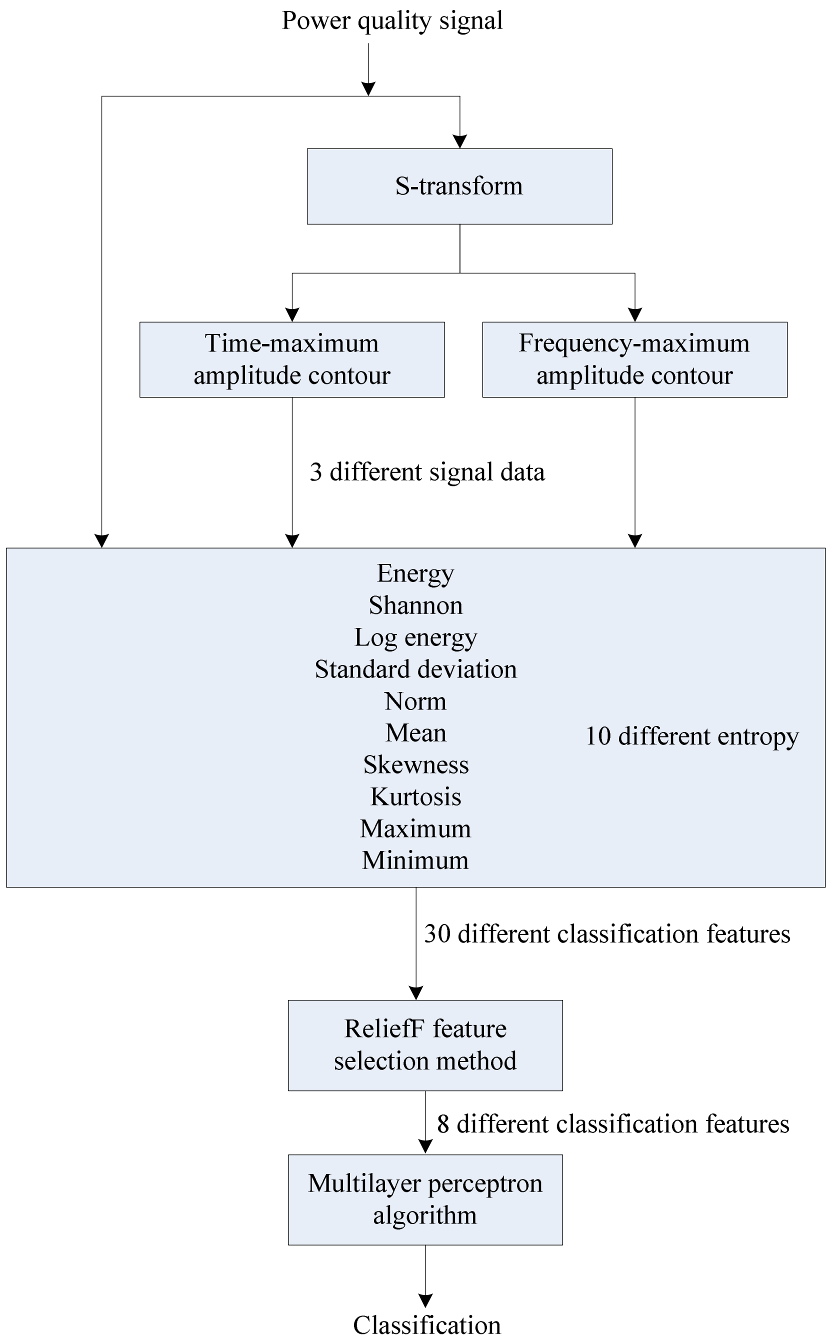

Figure 2. Classification method

Then, in order to obtain classification features, ST was applied to PQ disturbance signals. Two-dimensional (TF Time-Frequency) matrix of each signal was obtained after ST. This is an *NxM* matrix containing complex numbers. The columns of the matrix relate to time and the rows of the matrix relate to frequency. The time - the largest amplitude sequences (TmA- Time-maximum amplitudes) were obtained by searching for the largest values in the column values. The frequency - largest amplitude sequences (FmA- Frequency-maximum amplitude) were obtained by searching for the largest values in the row values.

Thirty (30) different classification features were obtained in total by taking 10 different entropy values of the PQ signal, the time-maximum amplitude signal and the frequency-maximum amplitude signal. These used entropies are Energy, Shannon, Log energy, Standard deviation, Norm, Mean, Skewness, Kurtosis, Maximum, and Minimum.

Then, PQ disturbances were classified by using 30 different classification features and MPA algorithm. Table 1 presents the simulation results obtained with 30 different classification features and MPA algorithm. There is 40 dB noise in the PQ signals in both the training and testing data.

Table 1. Simulation results obtained with 30 different classification features and MPA method (Training and testing data with 40dB noise)

	Training	**Testing**
Classification success %	99.88	98.88
Time taken to build model (s)	4.74	5.2
Time taken to test model (s)	0.01	0.02

As can be seen in the table, the success in the testing data was 98.88%. The WEKA program results showed that time taken to test model on the training data was 0.01 s and time taken to test model on the testing data was 0.02 s.

In addition, the results of the WEKA program showed that the time taken to create the model in the training data was 4.74 seconds. As can be seen in this table, a high classification success was achieved with 30 different classification features.

However, using the feature selection method, similarly high classification success can be achieved with less classification features. In this study, ReliefF feature selection method and MPA algorithm were used to provide a high classification success with less classification features. Using fewer classification features may shorten the training/testing times of the method.

First, the most effective features for classification were determined by the ReliefF method. This method was applied to the training data. Then, these features were added sequentially and the test success in the MPA method was examined. Here, the highest classification success was tried to be achieved by using the least classification feature. Table 2 shows the features selected by the ReliefF algorithm and the classification success of the MPA method.
As seen in this table, the highest classification success was achieved in the testing data with at least 8 selected features.

Table 2. Features determined by ReliefF method and classification success of MPA algorithm.

Number of different data	**Test classification success %**	Determined features
1	33.66	14
2	64.66	14,23
3	80.55	14,23,20
4	91.55	14,23,20,10
5	92.55	14,23,20,10,9
6	96.33	14,23,20,10,9,28
7	97.44	14,23,20,10,9,28,17
8	**98.22**	**14,23,20,10,9,28,17,26**
9	97.55	14,23,20,10,9,28,17,26,27
10	97.77	14,23,20,10,9,28,17,26,27,25
11	96.88	14,23,20,10,9,28,17,26,27,25,19

Table 3 shows the definitions of the determined features. According to Table 3, it can be seen that different entropy values of different signals were selected for classification.

Table 3. Description of the classification features determined by the ReliefF algorithm.

Dimension	**Feature**	**Signal Time-maximum amplitude Frequency-maximum amplitude**	**Entropy**
1	14	Time-maximum amplitude	Standard deviation
2	23	Frequency-maximum amplitude	Log energy
3	20	Time-maximum amplitude	Minimum
4	10	Signal	Minimum
5	9	Signal	Maximum
6	28	Frequency-maximum amplitude	Kurtosis
7	17	Time-maximum amplitude	Skewness
8	26	Frequency-maximum amplitude	Mean

Training and testing were carried out according to the 8 selected classification features in Table 3. Other classification features were removed from the database. The WEKA program was used again and the simulation results were examined. In Table 4, the simulation results obtained with 8 different classification features were shown.

Table 4. Simulation results obtained with 8 different classification features and MPA method (Training and testing data with 40dB noise).

	Training	**Testing**
Classification success %	98.88	98.22
Time taken to build model (s)	1.24	1.22
Time taken to test model (s)	0	0.01

As can be seen in Table 4, a classification success of 98.22% was obtained in the testing data with 8 selected classification features. In Table 1, a classification success of 98.88% was obtained in the testing data with 30 features. Table 1 and Table 4 showed that successful classification results were obtained by using 30 classification features with MPA and 8 determined classification features with MPA.

However, as seen in Table 1 and Table 4, the method (training/testing) was realized in a much shorter time with 8 classification features. For example, as seen in Table 1, when 30 classification features were used, the time required for the time taken to build the model was 4.74 s. As can be seen from Table 4, it takes 1.24 s with 8 classification features. Thus, a high classification success was achieved in a shorter time with 8 selected features. Therefore, in this study, it is proposed to use 8 classification features and MPA to classify PQ disturbances.
The MPA structure for the 8 determined features was shown in Figure 3.

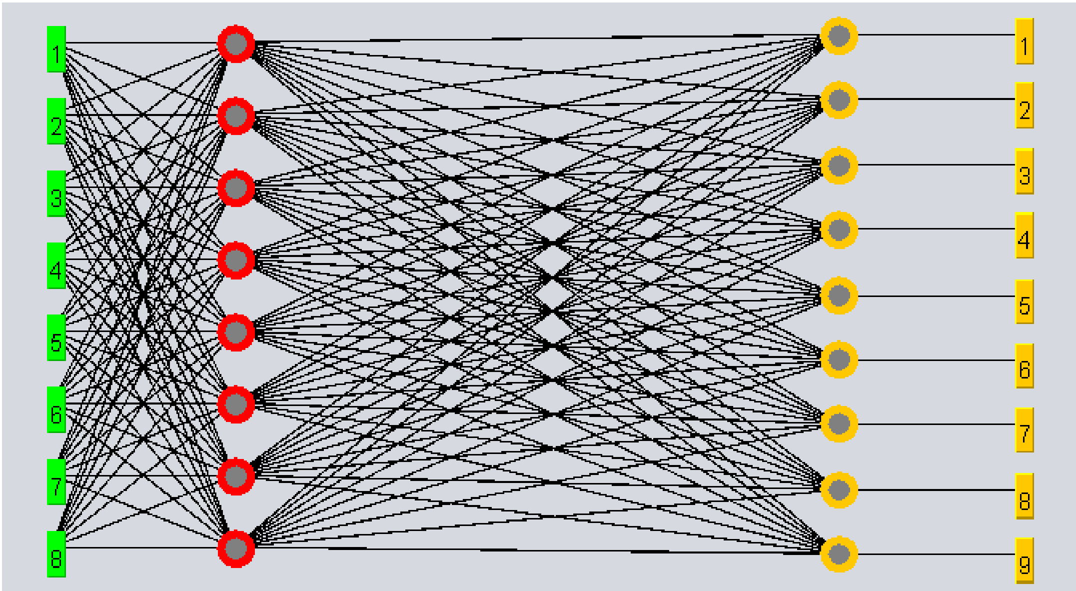

Figure 3. The MPA structure for the 8 determined features

At the same time, the proposed method should be tested on data with different noise levels. To do this, testing data with different noise were used. 30,35,40,45 and 50dB noise were added to the testing data. In the training data, 40 dB noise was used. Table 5 shows the classification success of the method for different noise levels.

Table 5. Classification success of 8 different classification features and MPA method in testing data with different noise levels (Training data with 40dB noise)

Test data noise level (dB)	**30**	**35**	**40**	**45**	**50**
Success (%)	79.22	94.55	98.22	98.66	98.66

Table 5 shows that the implemented method was effective in classifying PQ disturbances at different noise levels once trained. After the training was implemented, it was determined that the method was successful in noises of 35 dB and above.

In Table 6, the classification results of different methods in PQ signals with 40db noise were compared. As can be seen from this table, the proposed method has achieved an acceptable classification success.

Table 6. Comparison of the different methods (40dB noise results)

Ref	Signal processing	Classification algorithm	Feature selection method	Number of disturbances	Feature number	Success (40dB) %
[9]	Wavelet packet transform	Fuzzy k-nearest neighbour algorithm	GA	10	16	95.96
[8]	DWT	Probabilistic neural network	Artificial bee colony	16	9	98.6
Pro.	ST	MPA	ReliefF	9	8	98.22

6. CONCLUSIONS

Nowadays, many different methods were developed for classifying power quality signals. It is requested that these methods are as effective and simple as possible. In this study, a method based on Stockwell-transform, ReliefF feature selection method and Multilayer Perceptron Algorithm was applied for classification. As a result of the application of signal processing approach, 30 different classification features were obtained. However, at the present time, it is expected to achieve high classification success with less classification features. Therefore, ReliefF feature selection method was applied in the study. By using ReliefF feature selection method, 8 different classification features were determined. When the simulation results were examined, it shows that using 8 determined features instead of 30 features turns the classification method into a simpler structure and can make classification faster. The simulation results showed that the method was successful for classification. At the same time, all the obtained results showed that the proposed method provided an acceptable classification success.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could influence the work reported in this paper.

Author Contribution

Düzgün AKMAZ contributed 100% at every stage of the article.

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