AUTOMATIC POWER QUALITY DISTURBANCE CLASSIFICATION USING WAVELET, SUPPORT VECTOR MACHINE AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Abstract—This paper considers two important classification algorithms for to classify several power quality disturbances. Artificial Neural Network (ANN) and support vector machine (SVM). The last one is a novel algorithm that has shown good performance in general pattern classification. Nevertheless, Multilayer Perceptron Artificial Neural Network (MLPANN) is the most popular and most widely used models in various applications. Both are used for classify some disturbances under survey as: low frequency disturbances (such as flicker and harmonics) and high frequency disturbances (such as transient and sags).

Biorthogonal Wavelet Function is used as a base function for extract features of PQ disturbances. In addition, RMS value is used to characterize the magnitude of disturbances.

INTRODUCTION

Power quality (PQ) has been progressively more important for the industry and residential users in the last years owed to electromagnetic disturbances that cause big economic losses. Consequently, monitoring of PQ disturbances is essential to offer solutions to industrial and to electrical areas.

Actually a good number of the real recorded disturbances are analyzed manually by specialists. Nevertheless, is possible to use several techniques to identify and classify disturbances automatically. Thus, the specialists could center the attention directed toward resolving more complicated power quality problems [1].

Artificial intelligence techniques have had a great prosperity in the solution of the pattern classification problem. In the state of the art there are several classification techniques, the most used are: artificial neural network (ANN), fuzzy logic, genetic algorithms, case-based reasoning (CBR), Bayesian technique, quadratic discriminant analysis (QDA), linear discriminant analysis (LDA), decision trees and support vector machines (SVM), among others [2][3].

At the present, the utilization of artificial intelligence techniques is interrelated with the nature of the problem to resolve. For this reason, is difficult to make a decision or to generalize which one is the best technique among the aforementioned when they solve distinct problems with the same technique.

From now on some works of the state of the art related with classification techniques focused on the power quality disturbances studies are presented. In [4] the classification scheme is based on wavelet networks (WNs). This is a feedforward neural network that uses a wavelet function like layer’s activation function, and the backpropagation algorithm. This category of network can extract time-frequency information from the waveform. It is capable to classify momentary interruptions, oscillatory transients, and impulsive transients.

On the other hand [5] proposes a simple time-frequency based pattern recognition technique for classification and quantification of PQ disturbance waveforms. This technique consists on time-frequency analysis, feature extraction, and pattern classification. In this case it uses S-Transform to obtain the time-frequency characteristics of PQ events. For the classification of various power quality disturbances it uses a simple rule based system.

Artificial Neural Network is utilized as classifier in specific works like [6], where the inputs are current and voltage harmonic features. Furthermore, ANNs are used as classifier in [2], [7], [8], [9], [10] and others works that use input patterns obtained from Wavelet Transform. Throughout the precedent eight years a classification method called Support Vector Machine (SVM) has become progressively more accepted in power quality and others areas owed to its potent characteristics. A combination of wavelets and fuzzy support vector machines is used for [11] to automate detect and classify power quality disturbances. Fourier and wavelet transform are utilized to denoise the digital signals.

In this work, Wavelet Transform (WT) processing technique has been proposed for power quality monitoring given its time-frequency multiresolution analysis property. As well as root mean square (RMS) is used for extract characteristics.

In this article, minimal mathematical concepts of Discrete Wavelet Transform (DWT), ANNs and SVM are presented. Likewise the properties that make DWT, ANNs and SVM effective are also discussed. Finally, results of simulation and conclusions of this investigation are shown.

DISTURBANCES CLASSIFICATION

Two kinds of classifiers are analyzed and implemented in this work. Artificial neural networks and support vector machine. The patterns used as input are obtained from wavelet transform and RMS value.

Feature extraction

Wavelet Transform is suitable for feature extraction. Its properties, like limited effective time duration, band pass spectrum, waveform similar to disturbance and orthogonality, allow locating information in time and frequency domains. Thus, it is possible to obtain high
correlation when PQ disturbances occur and decompose these events into different components without energy aliasing.

The simple decomposition scheme of WT is conformed by low-pass and high-pass FIR filters, with impulse responses $a_m$ and $b_m$, respectively, followed by a two-decimation process. Therefore, if the samples $c_n$ of the signal are at the entrance of filters, the coefficients of approximation $c_{n-1}$ will be obtained at the output of the low-pass filter and so will be the detail coefficients $d_{n-1}$ at the output of the high-pass filter [12],[13] :

$$c_{n-1,k} = \sum_{m} a_{m-2k} c_{n,m}, \quad d_{n-1,k} = \sum_{m} b_{m-2k} c_{n,m}$$  \hspace{1cm} (1)

These Wavelet coefficients allow for reconstructing the signal by the insertion of zeros between samples. Then, these sequences are processed using low-pass and high-pass FIR filters. Fig. 1 shows the decomposition scheme.

![Fig. 1 Decomposition scheme of signal samples](image1)

It is possible to identify disturbances using wavelet coefficients energy. Each decomposition energy level represents a singular filter in the frequency domain, calculated energy represents particular characteristics of every disturbance. With this information is possible to differentiate several disturbances and some patterns are obtained using this decomposition.

Signal energy can be calculated from DWT coefficients in each decomposition level. Therefore, the signal energy distribution is determined for the frequency span of each decomposition level. Depending on the sampling frequency (Fs) and the wavelet function. Fig. 2 shows a decomposition scheme in 3 levels for a synthetic transient example.

![Fig. 2 Decomposition scheme in 3 levels for a synthetic transient](image2)

In the study realized by [2], some patterns are found using the energy of the wavelet decomposition coefficients and RMS value. The Biorthogonal 3.9 Wavelet function is utilized as mother wavelet for decomposition. As a result three patterns were obtained with 7, 8 and 9 positions each vector. All the steps to obtain the best wavelet function and the patterns are described clearly in [2].

In [14] PQ disturbances are classified as: electromagnetic transient, flicker, sags (dips), swells, unbalances, interruptions, notching and frequency variations. In this research five kinds of disturbances are analyzed: sag, swell, transient, flicker and harmonic. Fig. 3 shows a set of disturbances studied in this paper.

![Fig. 3 Power quality disturbances set under study](image3)

**Classification techniques**

This paper is based in the work developed in [2]; it studies four classification techniques and were implemented in order to classify disturbances automatically by using three kind of patterns based on WT. These techniques are: multilayer perceptron (MLP) and kohonen ANNs, Bayes and SVM. Only two strategies show good performance the MPL-ANN and MSV.

The ANN was trained with the following parameters: MLP network, feedforward performance function, tangent sigmoid activation function, three hidden layers, one exit layer and [7 6 4 1], [8 6 4 1], [9 6 4 1] neurons per layer for patterns 1, 2, 3, respectively. The output is a number between 1 and 5 that allows classifying 5 disturbance types. Network training was made with 500 patterns (100 patterns for each disturbance).

Fig. 4 shows a typical Artificial Neural Networks - Multilayer Perceptron.

![Fig. 4 Artificial Neural Networks - Multilayer Perceptron](image4)
previously mentioned is known as a supervised learning ANN because it is necessary to know the output corresponding to each input element. In recent years, SVM have shown good performance in patterns classification and recognition. In order to understand the way it operates, consider a data set distributed in two categories as it is shown in Fig. 5. The linear SVM look for a hyper-plane in such a way that the greatest number of points of the same category is located at the same hyper-plane side, whereas the distance (margin) of such categories to the hyper-plane is the greatest [15].

There is only one optimal separation hyper-plane (OSH), so the distance from OSH to the closest training pattern (support vector) is the maximum [15]. In order to carry out pattern linearization and to make the pattern classification easier, a Radial Base Function (RBF) \( k(x,y) = e^{-\frac{(x-y)^2}{\sigma^2}} \) was used as a kernel. RBF only requires a parameter (\( \sigma \)). In this work, crossed validation technique and the grid search were used [15]. Penalty parameters \( C = 2^{22} \) and \( \sigma = 0.7071 \) were obtained.

SVM and MLP schemes were tested with 1500 disturbances (300 per disturbance) randomly selected from the signal database. Success percentages are shown in Tables I and II.

### TABLE I - SUCCESS PERCENTAGES USING SVMs TO CLASSIFY 1500 DISTURBANCES

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Supp Vect</th>
<th>Train Exac =</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>164</td>
<td>93%</td>
</tr>
<tr>
<td>2</td>
<td>35</td>
<td>99%</td>
</tr>
<tr>
<td>3</td>
<td>76</td>
<td>98%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Supp Vect</th>
<th>Train Exac =</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sag</td>
<td>84.67</td>
<td>100.00</td>
</tr>
<tr>
<td>Swell</td>
<td>96.67</td>
<td>98.33</td>
</tr>
<tr>
<td>Transient</td>
<td>75.67</td>
<td>100.00</td>
</tr>
<tr>
<td>Flicker</td>
<td>100.00</td>
<td>94.33</td>
</tr>
<tr>
<td>Harmonic</td>
<td>100.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

### TABLE II- SUCCESS PERCENTAGES USING MLP ANNs TO CLASSIFY 1500 DISTURBANCES

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Success [%]</th>
<th>Pattern</th>
<th>Success [%]</th>
<th>Pattern</th>
<th>Success [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>48.00</td>
<td>2</td>
<td>72.33</td>
<td>3</td>
<td>88.00</td>
</tr>
<tr>
<td>2</td>
<td>72.33</td>
<td>2</td>
<td>88.00</td>
<td>4</td>
<td>68.00</td>
</tr>
<tr>
<td>3</td>
<td>98.67</td>
<td>2</td>
<td>88.00</td>
<td>5</td>
<td>96.00</td>
</tr>
</tbody>
</table>

### SIMULATION RESULTS

Two kinds of simulations were obtained in order to examine the performance of the classification system. In both kinds of simulations were utilized a MSV tool developed in MatLab®. The MSV classifier was trained on 500 synthetic disturbances, 100 signals per event type. Moreover 500 synthetic disturbances for MSV validation.

The MSV parameters utilized in both tests are: kernel function RBF, penalty parameters \( C = 2^{22} \) and \( \sigma = 0.7071 \), optimization method SMO (Sequential minimal optimization), decomposition method OVO (One Versus One) and 35 support vectors.

#### Controlled test classification

Knowing that the pattern 2 shows good result as is presented in Table II, a controlled test is obtained and presented in Table III. In this test 1500 disturbances were used, 300 signals for each disturbance type. Pattern 2 consists in a vector with 8 positions, 6 obtained from detail coefficient energy and 2 from RMS values [2]. The mother wavelet function used was Bior3.9 (Biorthogonal 3.9).

### TABLE III – CONTROLLED TESTS USING SVMS TO CLASSIFY 1500 DISTURBANCES

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sag</td>
<td>300</td>
</tr>
<tr>
<td>Swell</td>
<td>295</td>
</tr>
<tr>
<td>Transient</td>
<td>300</td>
</tr>
<tr>
<td>Flicker</td>
<td>0</td>
</tr>
<tr>
<td>Harmonic</td>
<td>0</td>
</tr>
</tbody>
</table>

Table III shows in this case, three swells were confused with sags and two swells with transients. To improve the patterns is necessary for find better results.

#### Noise environment classification

Another realized test in this work (second test) take three different kind of signal noise ratio (SNR) to measure the effectiveness of classifier in noise environment. As shown in Table IV, success percentage of classification for 1500 disturbances with 3 different noise environment. These results showed that SVM can classify almost 100% all disturbances except swell under SNR of 40 and 60 decibels (dB), therefore SVM has high immunity for these specifics SNR. For a SNR of 20 dB, it presents success percentage lowers than 70% for harmonic and 95% for disturbances such as swell and transient.
TABLE IV- SUCCESS PERCENTAGES TO CLASSIFY 1500 DISTURBANCES IN NOISE ENVIRONMENT

<table>
<thead>
<tr>
<th></th>
<th>SNR 20dB</th>
<th>SNR 40dB</th>
<th>SNR 60dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sag</td>
<td>99</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Swell</td>
<td>95</td>
<td>98</td>
<td>98</td>
</tr>
<tr>
<td>Transient</td>
<td>95</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Flicker</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Harmonic</td>
<td>71</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

CONCLUSIONS

A PQ disturbance identification and classification technique which combines advantages of disturbances identification strategy based on DWT and RMS, with the advantages of the ANNs and SVM to classify information automatically was implemented in a toolbox in MatLab®. A database of 19 430 synthetic signals was generated, with different disturbances and different signal variations for training, validating and evaluating each classification scheme. The parameters for the generation of synthetic disturbances are obtained according to [14]. SVM classifier could be the best classifier for patterns obtained in this work. It takes less time to classify the same data than MPL-ANN. Though, MLP-ANN displays good performance in success percentage of classification. It is necessary to do more training and tests to find an MLP-ANN classifier with better characteristics than obtained in this research. Controlled test classification permitted identifies the kind of disturbances that present similar structure in the pattern. It allows improve the pattern characteristics. Is possible add or consider others elements (or transformations) of the disturbances.

As a conclusion SVM classifier presented high immunity for SNR ≥ 40 as shown in Table IV, success percentage under noise environment of 40 and 60 dB is 100% for all of the disturbance types, with exception of swell that has 98%. The reason of this is mainly because swell pattern is similar to transient pattern when the magnitude of both is minor.

REFERENCES


BIographies

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