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Influence of Signal Pre-Processing in the Efficiency of Algorithms Based on Neural Networks for Disturbance Classification

Manoel F. de Medeiros Jr./ Crisluci K. S. Santos/ José T. de Oliveira/ Paulo S. da M. Pires/ Jorge D. de Melo/ Adrião D. Dória Neto
DCA
UFRN
Natal, Brasil

José J. A. L. Leitão
CHESF
Recife, Brasil

***Abstract*—Post dispatch analysis of signals obtained from digital disturbances registers provide important information to identify and classify disturbances in power systems, looking for a more efficient management of the supply. In order to enhance the task of identifying and classifying the disturbances - providing an automatic assessment - techniques of digital signal processing can be helpful. The Wavelet Transform has become a very efficient tool for the analysis of voltage or current signals, obtained immediately after disturbances occurrences in the network. This paper presents a methodology based on the Discrete Wavelet Transform to implement this process. It uses a comparison between distribution curves of signals energy, with and without disturbance. This is done for different resolution levels of its decomposition in order to obtain descriptors that permit its classification, using artificial neural networks.**

I. INTRODUCTION

An efficient analysis of disturbances registered in power electric systems is fundamental to evaluate the electric power quality indexes. Aiming to obtain adequate measures to prevent or to correct power quality disturbances, these disturbances must be previously identified and classified. However, in general, a simple inspection of a signal is not enough to identify the kind of phenomenon present in the waveforms. Moreover, the big amount of data makes impracticable a visual inspection of all registered signals, demanding therefore an automatic assessment.

This paper presents a procedure for obtaining an automatic classification of the most important disturbances - that imply in degradation of power quality - using Discrete Wavelet Transform and Artificial Neural Networks (ANN).

The Discrete Wavelet Transform has become a very efficient tool for the analysis of voltage or current signals, registered immediately after disturbances occurrences in the network. Useful information about the signal can be obtained from wavelet transform properties to define descriptors for the selected disturbances. The main advantages of this transform are: the multi-resolution decomposition, fast signal restoration, and use of algorithms with low computational complexity. The descriptors were used to classify the disturbances through Artificial Neural Network architecture.

II. ANALYZED SIGNALS

The data base used in this work is composed of voltage disturbances signals obtained from registering equipments (oscillographs) installed at different points of the Northeastern Brazilian Power Generation and Transmission Company – CHESF. The sampling rate of the equipments was 128 samples by cycle. Four disturbances types in the network were analyzed: transients, harmonics distortions, voltage swell and sag.

III. FUNDAMENTALS OF DISCRETE WAVELET TRANSFORM THEORY

One of the main goals of the signal processing analysis is to extract important information about the process in which the signal is associated. Usually, this analysis is done using some kind of signal transformation, which is based in signal representation and reconstruction techniques. The wavelet analysis [1], like the Fourier analysis, is based in base functions. While the Fourier's Transform uses sinusoidal functions, by wavelet analysis the base function can be chosen according to many *families* of waveforms. These functions are called *analysis wavelets* or *mother-wavelets*.

The Discrete Wavelet Transform (DWT) consists in modifying a discrete signal in the time domain to the wavelet domain. This can be carried out using the *lifting* scheme ([2], [3], [4]), in which a time sampled signal is transformed to the wavelet domain by digital filtering techniques. The lifting scheme main characteristic is that the whole algorithm is derived in the time domain, in contrast to the traditional approach which is in the frequency domain. This scheme, illustrated in Figure 1, involves three main stages: SPLIT, PREDICT and UPDATE [4].

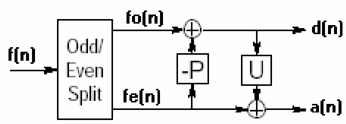

Figure 1. The Lifting scheme

The SPLIT stage *splits* the input signal, f(n), in two subsets, one with the even indexes elements, fe(n), and the other with odd indexes elements, fo(n). Then,

$$fe(n) = f(2n)$$

$$fo(n) = f(2n+1)$$

By the PREDICT stage the wavelets coefficients d(n) are generated by the difference between fo(n) and fe(n), with the latest using the prediction operator P: This operation is represented by the equation:

$$d(n) = f_o(n) - P(f_e(n)).$$

The UPDATE stage generates the wavelets coefficients a(n) that represent an approximation of the original signal f(n). This coefficient is results from the sum of fe(n) with the update operator U for d(n):

$$a(n) = f_e(n) + U(d(n)).$$

A more detailed explanation of the *lifting* procedure can be found in references [3] and [4].

IV. METHODOLOGY

This section shows how to proceed toward to obtain a reliable classification of power quality disturbances by an automatic way. In summary, the whole process is divided into four main stages, as shows the scheme of Figure 2.

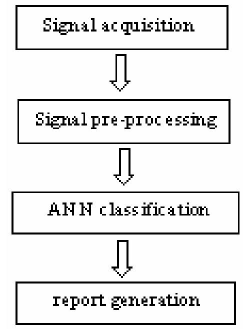

Figure 2. Schematic diagram of the stages developed in the work.

The first step consists in the acquisition of voltage signals samples to be analyzed. The following step corresponds to the conditioning of these samples. The recorded signals must be pre-processed in such a way that peculiar characteristics, which are present in all kinds of disturbances, can be easily identified, and converted to descriptors to be used in an Artificial Neural Network in order to allow a classification.

The proposed pre-processing stage is based on the simple steps reported in ref. [5]. It was developed and programmed for utilization in Scilab platform. The procedures can be summarized in four stages:

- Step 1: consists in decomposing the disturbance signal in different resolution levels, resulting in various wavelet coefficients;
- Step 2: corresponds to the calculation of the energy concentrated in each decomposition level;

In Physics and Engineering, Parseval's theorem [7] is often written as:

$$\int_{-\infty}^{\infty} |x(t)|^2 \, dt = \int_{-\infty}^{\infty} |X(f)|^2 \, df \qquad (1)$$

where $X(f) = \Im\{x(t)\}$ represents the continuous Fourier transform (in normalized, unitary form) of *x(t)* and *f* represents the frequency component of *x*.

The interpretation of this form of the theorem is that the total energy contained in a waveform *x(t)* summed across all of time *t* is equal to the total energy of the waveform's Fourier Transform *X(f)* summed across all of its frequency components *f*. Although one can prove this result from purely *mathematical* considerations, it is actually a statement of the energy conservation principle.

For discrete time signals, the theorem becomes:

$$\sum_{n=-\infty}^{\infty} |x[n]|^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} |X(e^{j\phi})|^2 \, d\phi \qquad (2)$$

where X is the discrete-time Fourier transform (DTFT) of x and φ represents the angular frequency (in radians per sample) of x.

For the discrete Fourier transform (DFT), the relation becomes:

$$\sum_{n=0}^{N-1} |\, x[n]\,|^2 = \frac{1}{N}\sum_{k=0}^{N-1} |\, X[k]\,|^2 \qquad (3)$$

where $X[k]$ is the DFT of $x[n]$, both of length N.

If the discrete transform of the signal is accomplished in wavelet domain, the first member of equation (3) must equal the sum of the energy contents of all signal components in this domain.

$$\sum_{n=1}^{N} |\, f(n)\,|^2 = \sum_{n=1}^{N} |\, a_j(n)\,|^2 + \sum_{j=1}^{J}\sum_{n=1}^{N} |\, d_j(n)\,|^2 \qquad (4)$$

Where:
f(n): recorded signal, sampled in time domain;
N: corresponds to the amount of signal samples;

$\sum_{n=1}^{N} |\, f(n)\,|^2$: energy of the analysed signal;

$\sum_{n=1}^{N} |\, a_j(n)\,|^2$: energy *concentrated* in the approximate version of level "j" of the analyzed signal;

$\sum_{j=1}^{J}\sum_{n=1}^{N} |\, d_j(n)\,|^2$: sum of the energies concentrated in detailed versions of levels from 1 until "J" of the analysed signal.

- Step 3: repeats steps 1 and 2, just for the sinusoidal component of the reference signal, which is obtained from the first cycle of the actual registered signal. The remaining cycles are inferred using the least-square method, applied to the pre-fault registers.

- Step 4: finally, a comparison between the energies concentrated in each level of both disturbance signal (step 2) and sinusoidal signal (stage 3) is carried out. This is done evaluating the percent difference between the energy distributions of the signals. The calculation is carried out according to the equation:

$$dp\,(j)(\%) = \left[\frac{en\_dis\,(j) - en\_ref\,(j)}{\max(\,en\_ref\,)}\right] * 100 \qquad (5)$$

The presented methodology involves descriptors to define the characteristics peculiar to the different studied disturbances [6].

The following step consists in the disturbance classification. This done using an C architecture. As a result, the correct classification of the disturbance present in the input signal is obtained.

V. PRE-PROCESSING STAGE

Comparing both results obtained from former and from the actual pre-processing algorithms it can be concluded that a significant progress was reached.

The recorded signals used for the analysis have 1792 samples and 14 cycles. The sample rate of theses signals were 128 samples/cycle. For application of the former pre-processing algorithm, the amount of samples was reduced to 1024, discarding the three first and three latest cycles. In order to obtain the reference signal, the first cycle is adjusted to a sinusoidal wave form by extrapolation, using the least square method.

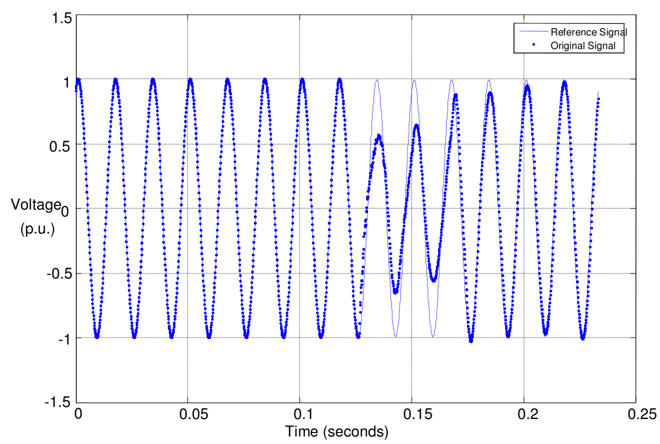

Figure 3. Voltage signal with sag used to construct the Reference Signal.

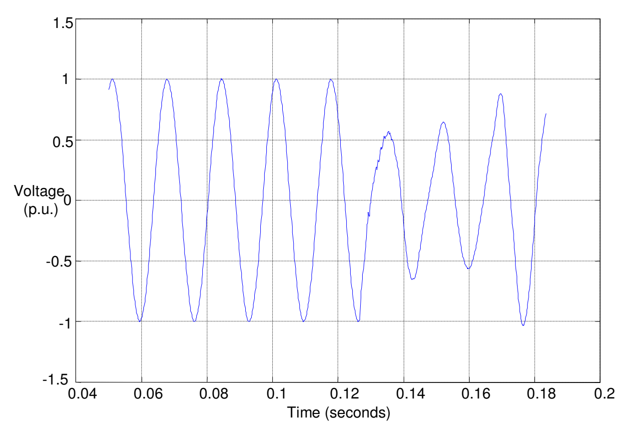

Figure 4. Disturbance Signal with 1024 samples, used in pre processing signal stage.

The main focus of this work is a new improvement introduced in the pre-processing algorithm. Once not all cycles of the recorded signal contain disturbances, a set of rules was elaborated to extract just the part of interest. This way, the remaining samples are discarded, as shown in Figure 5.

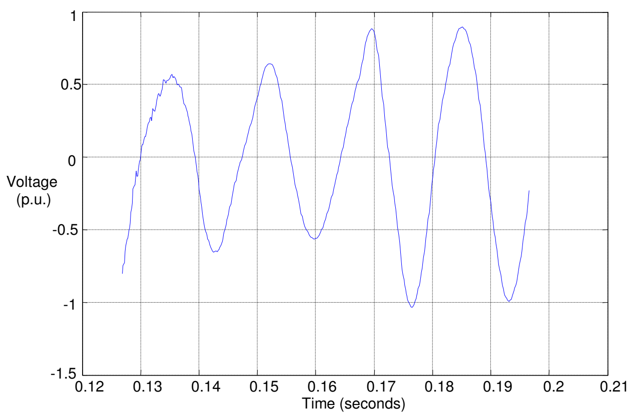

Figure 5. Signal used in pre-processing, containing just the disturbance.

Once just the samples containing the disturbance are used to extract descriptors, an increase in the classification is to be expected. Moreover, if distortions are present at the beginning or at the end of the record, the proposed algorithm avoids the possibility of disregarding an important part of the signal, as shows Figure 6.

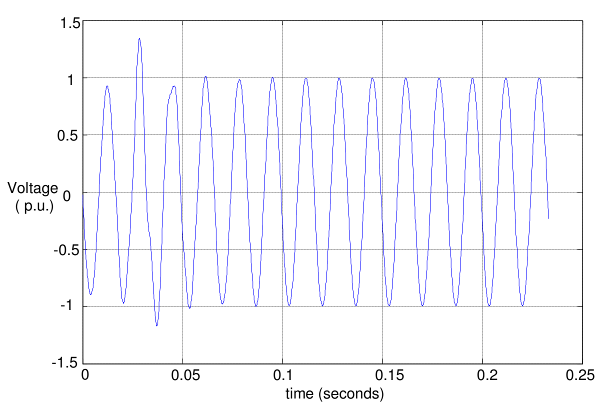

Figure 6. Recording signal (1792 samples) with the disturbance in the first cycles.

A further algorithm was developed to obtain the reference signal, extracting information from the proper recorded samples. A significant cycle of the recorded signal, related to amplitude and distortion, is selected to become a reference, as shown in Figure 7. This reference cycle is replicated until the amount of necessary samples is reached. This can be observed in Figure 8.

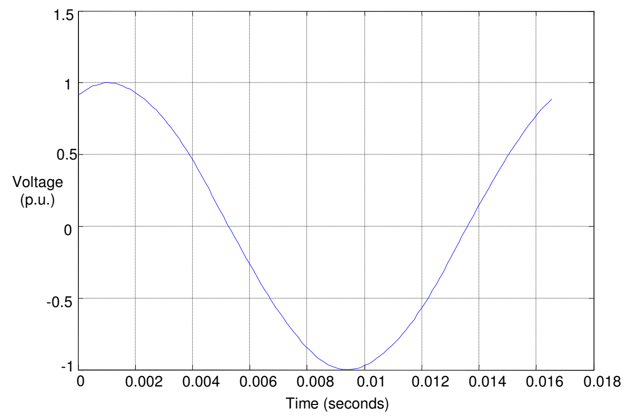

Figure 7. Reference cycle, according to the above mentioned rules

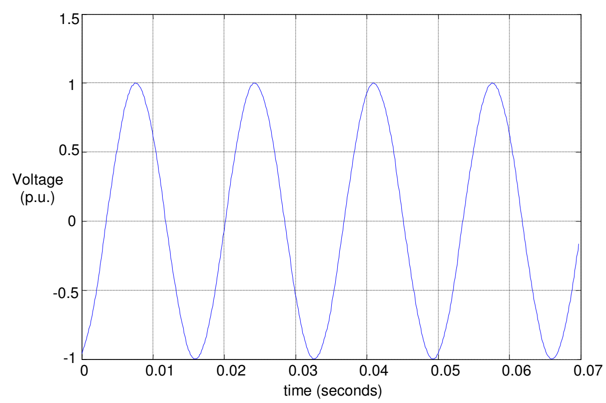

Figure 8. Reference signal composed replicating the reference cycle

VI. ARTIFICIAL NEURAL NETWORK FOR DISTURBANCE CLASSIFICATION

The procedure adopted for disturbances classification by means of a neural network structure [8] is based on descriptors obtained from the signals decomposition using *wavelets*. For the disturbances analyzed in this work, the descriptors were defined as:

$$desc = \begin{bmatrix} \mathrm{desc}_1 \\ \mathrm{desc}_2 \\ \mathrm{desc}_3 \\ \vdots \\ desc_{10} \end{bmatrix}$$

Where:

TABLE I: DESCRIPTORS

$desc_1$	Biggest (absolute) percentage difference of energies between the different wavelet decomposition levels of the signals with and without disturbance;
$desc_2$	Level where occurred the biggest percentage difference;
$desc_3$	Second biggest percentage difference;
$desc_4$	Level where occurred the second biggest percentage difference;
$desc_5$	Third biggest percentage difference;
$desc_6$	Level where occurred the third biggest percentage difference;
$desc_7$	Fourth biggest percentage difference;
$desc_8$	Level where occurred the fourth biggest percentage difference;
$desc_9$	Fifth biggest percentage difference;
$desc_{10}$	Level where occurred the fifth biggest percentage difference;

Four disturbances classes were defined, according to:

$$class_{dist} = \begin{bmatrix} class_1 \\ class_2 \\ class_3 \\ class_4 \end{bmatrix}$$

Where:

TABLE II: CLASSES

Descriptors	
$class_1$	Voltage sag
$class_2$	Voltage swell
$class_3$	Harmonics
$class_4$	Transitories

The classification was done by means of a neural network **Multi-Layers Perceptron (MLP)**. The training was carried out using the Resilient Backpropagation algorithm (Rprop). Different architectures types were analyzed (10:20:4, 10:40:4, 10:60:4, 10:80:4 e 10:100:4). A total of 800 standards were used for the training, whereas 344 standards were used for the validation.

VII. RESULTS AND COMPARISON

This section presents the obtained results, using both pre-processing algorithms. A comparison is carried out in order to assign the efficiency of the new algorithm.

Tables III and IV summarize the success rates obtained for the validation set, considering different architectures of the neural network, for the former and for the actual algorithm, respectively. The biggest success rate by the old pre-processing algorithm was 89,25% whereas by the new algorithm this rate was 99,70%. Therefore, a significant raise (about 10%) in the success rate was obtained.

TABLE III
SUCCESS RATES FOR DIFFERENT ARCHITECTURES OF THE NEURAL NETWORK (RPROP) FOR THE FORMER PRE-PROCESSING ALGORITHM

Architecture	10:20:4	10:40:4	10:60:4	10:80:4	10:100:4
	85.34%	87.62%	87.95%	88.60%	89.25%

TABLE IV
SUCCESS RATES FOR DIFFERENT ARCHITECTURES OF THE NEURAL NETWORK (RPROP) FOR THE ACTUAL PRE-PROCESSING ALGORITHM

Architecture	10:20:4	10:40:4	10:60:4	10:80:4	10:100:4
	90.69%	99.70%	84.59%	89.53%	82.,55%

Table V shows the Confusion Matrix obtained for the best architecture presented in Table IV. This matrix is commonly used to evaluate the classification efficiency, comparing the identification provided by the neural classifier with the real one. The diagonal elements of the matrix show the number of disturbances correctly classified.

TABLE V
CONFUSION MATRIX OBTAINED FOR PMC NETWORK USING THE RPROP ALGORITHM FOR THE BEST ARCHITECTURE OF TABLE IV

Disturbances	**Sag**	**Swell**	**Transient**	**Harmonics**
Sag	**86**	0	0	0
Swell	0	**85**	1	0
Transient	0	0	**86**	0
Harmonics	0	0	0	**86**

As shown in Table V voltage sag, transients and harmonics obtained a success rate of 100%, whereas voltage swell was classified with success rate of 98.8%. In this case, 85 standards, in a set of 86, were well classified.

VIII. CONCLUSIONS

The objective of this work was to present a procedure to classify disturbances responsible for a reduction in power quality. The developed methodology considered four event types, obtained by means of recording equipments. From the signals pre-processing algorithm was possible to define descriptors that permitted to characterize a standard for each type power quality disturbance, which was used as input for neural classifier.

The improvements introduced in the pre-processing algorithm were of great importance to increase the success rates in the classification. It can be concluded from the results presented in previous section.

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