AUTOMATIC POWER QUALITY DISTURBANCES DETECTION AND CLASSIFICATION BASED ON DISCRETE WAVELET TRANSFORM AND SUPPORT VECTOR MACHINES

Valdomiro VEGA
UIS – Colombia
valdomirovega@ieee.org

César DUARTE
UIS – Colombia
cedagua@uis.edu.co

Gabriel ORDÓÑEZ
UIS - Colombia
gaby@uis.edu.co

ABSTRACT

In this paper some patterns based on discrete Wavelet transform are studied for detection and identification of both, low frequency disturbances, like flicker and harmonics, and high frequency disturbances, such as transient and sags. Daubichies4 Wavelet function is used as a base function to detect and identify due to its frequency response and time localization information properties. Based on these patterns, power quality disturbances are automatically classified by support vector machines (SVM). Thus, Radial Base Function (RBF) was used as a kernel, because RBF requires only two parameters (σ and C) and cross validation technique and grid search were used in this work. SVM exhibit a good performance as classifier (90 percent of success for most disturbances) in spite of similitude between some disturbance patterns.

INTRODUCTION

Electromagnetic disturbances cause big economic losses for industry and residential users. Because of this, monitoring of power quality (PQ) disturbances of electrical energy is fundamental to offer solutions to industrial and to electrical areas. Wavelet Transform (WT) processing technique has been proposed for power quality monitoring given its time-frequency multiresolution analysis property.

WT 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.

There are several studies [1]-[3] where WT is used for detecting and identifying disturbances with Wavelet function Daubichies 4. Likewise, neuronal networks have been used to classify different disturbances from its WT. [4] shows a method of PQ disturbances detection and classification based on heuristic rules. However, there are no references about using other techniques of classification like Bayesian or support vector machines (SVM) for PQ disturbances.

In this article, mathematical concepts of Discrete Wavelet Transform (DWT) are described. The properties that make DWT effective are also discussed. Then, strategies for PQ disturbances detection and identification by using DWT are studied. Strategies used for automatic classification of these disturbances are also presented. Finally, results of simulation and conclusions of this investigation are shown.

DISCRETE WAVELET TRANSFORM

Fourier Transform (FT) only allows the study of a fixed interval of a transient disturbance, but it is not possible to know its location. Then, a dynamic scheme is necessary where, in the same coordinates system, the width of time and frequency windows can be varied simultaneously preserving resolution in both domains (time and frequency). This characteristic is reached by means of the time-frequency multiresolution analysis that WT makes.

The Continuous Wavelet Transform (CWT) is defined in (1),[6]:

$$(W_\psi x)_{(b,a)} = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt = \left\langle x(t), \psi_{a,b}(t)\right\rangle \tag{1}$$

Where < , > denotes the inner product operation; $\psi(t)$ is the "mother Wavelet function" or analysis Wavelet of CWT. In (1) is considered that Wavelet function is a real value signal. The time location is determined by the term:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

Where $\psi_{a,b}(t)$ is a set of Wavelets generated from the "mother Wavelet function" $\psi(t)$, which expands and attenuates, or compresses and amplifies as a increases or diminishes, respectively. In addition, $\psi(t)$ moves in the time domain as b changes.

The DWT is obtained by considering that parameters of scaling a and shifting b take discrete values: $a=a_o^j$, $b=k\,b_o\,a_o^j$, with $j, k \in Z$, $a_o > 1$ and $b_o > 0$. By replacing these values in (1) yields [6]:

$$(W_\psi x)_{(j,k)} = \frac{1}{\sqrt{a_0^j}}\int_{-\infty}^{\infty} x(t)\psi\left(a_0^{-j}t-kb_0\right)dt = \left\langle x(t), \psi_{j,k}(t)\right\rangle \tag{3}$$

Where the set of Wavelet functions $\psi_{j,k}(t)$ is given by:

$$\psi_{j,k}(t) = \frac{1}{\sqrt{a_0^j}}\psi\left(a_0^{-j}t-kb_0\right) \tag{4}$$

However, for some appropriate "mother Wavelet functions" and factors a_o and b_o, it is possible to express $x(t)$ like a linear combination of Wavelet functions $\psi_{j,k}(t)$, scaled and shifted. It is required that functions $\psi_{j,k}(t)$ be orthonormal [5], [6].

ALGORITHMS

The decomposition scheme is conformed by low-pass and a 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 low-pass filter and so will be the detail coefficients d_{n-1} at the output of high-pass filter [5]:

$$c_{n-1,k} = \sum_m a_{m-2k} c_{n,m}; \quad d_{n-1,k} = \sum_m b_{m-2k} c_{n,m} \qquad (5)$$

With these Wavelet coefficients it is possible to reconstruct the signal by inserting zeros between samples. Then, these sequences are processed using low-pass and high-pass FIR filters. In Fig. 1, scheme of decomposition is shown.

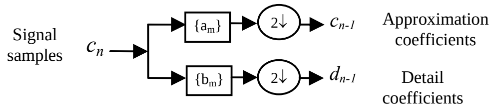

Fig. 1. Scheme of decomposition of signal samples.

DISTURBANCES DETECTION AND IDENTIFICATION

In [7] PQ disturbances are classified as: electromagnetic transient, flicker, sags (dips), swells, unbalances, interruptions, notching and frequency variations.

Each one of these disturbances can be detected by using detail sequence from the first wavelet decomposition level (Fig. 1). By applying again the decomposition scheme to an approximation sequence is possible to find new details with smaller frequency span than that from the detail sequence previously calculated. Thus, different detail levels of the signal (or frequency intervals) can be analyzed.

Fig. 2 shows a set of disturbances studied in this paper and Fig. 4 displays their respective detail sequences from the first level with Wavelet function daubechies4 "db4". It can be noted that in Fig. 3 is possible to detect the beginning and/or the end of each disturbance in the first level of detail. This is because beginning and end of disturbance contain high frequencies, which are detected in the first level of detail.

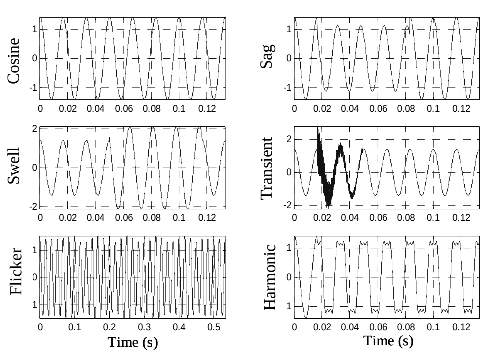

Fig. 2. Disturbances set under study.

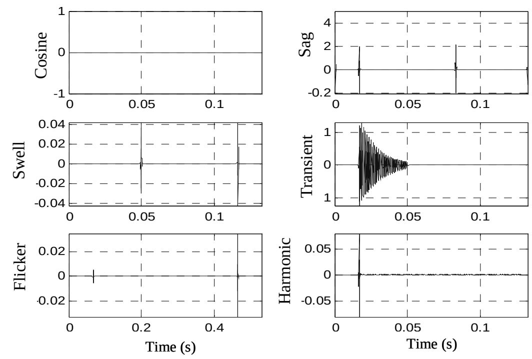

Fig. 3. Disturbances detail at first level using daubechies 4.

It is possible to identify disturbances using Wavelet coefficients energy. Signal energy can be calculated from DWT coefficients in each decomposition level. Therefore, it is possible to know signal energy distribution in the frequency span of each decomposition level. Depending on sampling frequency (Fs) and Wavelet function (db4), the bandwidth of each decomposition level is determined.

[1] proposes a disturbance identification strategy that calculates energy distribution deviation for each decomposition level. Coefficients energy of each detail level (detail sequence energy) is calculated, for both the pure sinusoidal signal and the signal with disturbances, then they are compared by the following expression:

$$dp(j)(\%) = \left[\frac{En\_dist(j) - En\_ref(j)}{En\_ref(m)}\right]*100 \qquad (6)$$

Where *dp(j)(%)* is the deviation between the energy of the signal with disturbances *En_dist(j)* and its corresponding fundamental sinusoidal signal energy *En_ref(j)*, at each wavelet transform decomposition level *j*. *En_ref(m)* is the greatest value of the fundamental sinusoidal signal energy which may corresponds to a different level *m*.

However, [1] does not propose any method to classify the different types of disturbances.

This identification strategy, described above, has been adopted in this article, since it allows to obtain disturbance patterns with a low degree of resemblance between them (such as it appears in Fig. 4 by evaluating (6)), which is desirable for their classification. Nevertheless, it must be noticed that swell and flicker patterns have similar characteristics. Likewise, when a given disturbance is shifted in time domain its pattern magnitude reveals significant variations. This is explained by the shift no-invariant property of WT. Because of this, it was necessary to scale patterns in order to obtain standardized magnitudes.

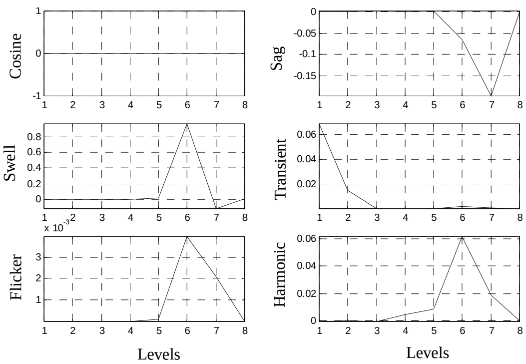

Fig. 4. Disturbance patterns.

Fig. 4 presents patterns until decomposition level 8. A sampling frequency of 7 680 Hz has been used. Then, frequencies at level 8 ideally span from 15 to 30 Hz and disturbances have no relevant information in this interval.

DISTURBANCES CLASIFICATION

Artificial Neural Networks (ANNs), Fuzzy Logic or the combination of them have been proposed for PQ disturbances classification in [2], [4], among others. On the other hand, Bayesian technique [8] and support vector machines (SVM) have been used as pattern classifiers ([9]), but not specifically for PQ events.

In this study, 4 classification techniques were implemented in order to automatically classify disturbances by using their patterns based on WT. These techniques are: multilayer perceptron (MLP) and kohonen ANNs, Bayes and SVM.

An ANN was trained with the following parameters: MLP network, feedforward performance function, tangent sigmoid activation function, 3 hidden layers, one exit layer and [8 6 4 1] neurons by layer. The 8 input are patterns based on 8 WT decomposition levels. 5 disturbance types sampled at a rate of 128 samples per 60 Hz cycle (s/c) were studied. The output is a number between 1 and 5 that allows classifying these 5 disturbance types. ANN parameters were determined according to [10]. Network training was made with 5 600 inputs (700 inputs for each input layer neuron) and 700 outputs. Training validation was accomplished with 1 680 inputs (210 for each neuron at entrance layer) and 210 outputs.

In this work, a database with 19 430 synthetic signals was generated. A number of variations were considered to characterize different disturbances (magnitude, starting point, duration, frequency, etc.) according to [7].

Signals used for training, validating and evaluating ANN performance were selected from this signal database. However, each signal was used only once.

The ANN previously mentioned is known as a supervised learning ANN because it is necessary to know the output corresponding to each input element.

A Kohonen network was trained in this work. Kohonen network belongs to competitive networks category or self organizing maps (SOM), that is, non-supervised learning network type. These networks have a two-layer architecture (input-output) (a single connections layer), linear activation functions and unidirectional information flow (cascade networks). This model is called LVQ (learning vector quantization) [11]. This network was trained with the same input of that of the previous network, but output data set was not necessary. The maximum allowed error was set to 0,001 and 800 iterations were executed.

Bayes decision technique is the base of statistical methods for patterns recognition. This technique considers K classes denominated w_k, and one input vector X. $P(w_k/X)$ is the *aposteriori* probability that can be calculated with Eq. (7), [8]:

$$P(w_k / X) = \frac{P(X / w_k) \cdot P(w_k)}{P(X)} \qquad (7)$$

$P(w_k)$ is w_k class probability (*apriori* probability). $P(X/w_k)$ is X probability distribution conditioned to a particular w_k class. $P(X)$ is X probability distribution.

The decision rule can be stated as: "the correct class is the one that displays the greatest *aposteriori* probability". From (7) a discriminating function given in (8) was implemented in this work.

$$g_k(X) = P(X / w_k) \cdot P(w_k) \qquad (8)$$

This simplification is possible since $P(X)$ is equal to 20% because there are 5 classes (disturbances).

In recent years, SVM have shown good performance in patterns classification and recognition [9]. In order to understand the way it operates, consider a data set distributed in two categories as it is shown in Fig. 6. The linear SVM look for a hyper-plane in such a way that the greatest number of points of the same category are located at the same hyper-plane side, whereas the distance (margin) of such categories to the hyper-plane is the greatest [9], [11].

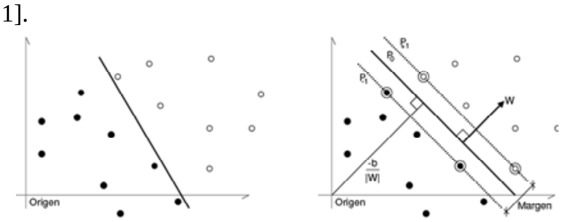

Fig. 5. Hyperplane of separation

There is only one optimal separation hyper-plane (OSH), so the distance from OSH to the closest training pattern (support vector) is the maximum [9], [11]. In order to carry out pattern linearization and to make the pattern classification easier, a Radial Base Function (RBF) $k(\bar{x},\bar{y}) = e^{\left(-\frac{|\bar{x}-\bar{y}|^2}{2\sigma^2}\right)}$ was used as a kernel. RBF only requires a parameter (σ). In this work, crossed validation technique and the grid search were used [9]. Parameters of penalty C = 2 048 and σ= 0,5 were obtained. Classification results appear in Table I.

SIMULATION RESULTS

The scheme was tested by 200 disturbances of 5 types, randomly selected from the signal database. Success percentages are shown in Table I. Each one of 5 disturbance categories were sampled at 128 s/c (Fs=60*128 Hz).

As shown in Table I, success percentage for Kohonen LVQ network is, for most of the types of disturbances, less than 60%. This could mean that it is not a good classifier for these patterns, while MLP network has 90% of success for most of the types of disturbances. Flicker pattern is similar to swell pattern; this might explain why its success percentage is less than 90%.

TABLE I
SUCCESS PERCENTAGES FOR MULTILAYER PERCEPTRON (MLP) AND KHONEN LVQ NEURAL NETWORKS, BAYES AND SUPPORT VECTOR MACHINES.

Disturbances	*MLP [%]*	*K- LVQ [%]*	*BAYES[%]*	*SVM [%]*
Sag	93	55	92	**98**
Swell	97	56	51	**98**
Flicker	86	90	85	**100**
Osc.Transient	79	60	0	**99**
Harmonic	95	50	0	**100**

Therefore, the best classification strategy is based on SVM with 248 Support Vectors and 96,29% training accuracy. SVM performance is followed by that of MLP ANN. MLP ANN could be improved by modifying some of its parameters and/or input patterns. The results above point out that Bayesian classifier (linear classifier) are not good to classify these disturbance patterns. The reason for this is that input data are not close to a normal distribution. Jarque - Bera test was applied to the data set and it resulted in 89% of rejection, that is, input data are not close to a normal distribution.

CONCLUSIONS

A PQ disturbance detection and identification technique which combines advantages of disturbances identification strategy based on DWT, with the advantages of the ANNs and SVM to classify information automatically was implemented. Once the disturbance is detected, it is possible to locate it from the detail sequence at first decomposition level (Fig. 5).

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 success percentage obtained in the evaluation of the strategy of detection, identification and classification, for most of the disturbances categories was better than 80% and 90%, in spite of shifting no-invariant property of WT.

SVM could be the best classifier for patterns obtained in this work. Though, ANNs (supervised) display good performance. Since no classifier is completely efficient when patterns of different disturbances are very similar, it is necessary to use a classification strategy that considers other signal parameters.

Bayes technique decision is not a good classifier for the patterns used in this work because input data are not close to a normal distribution.

REFERENCES

[1] J.W. Resende, "Identification of power quality disturbances using the MATLAB wavelet transform toolbox". PhD. Dissertation, Federal University of Uberlandia (MG)-Brazil. pp.8 2001. Available: http://www.ipst.org/TechPapers/2001/IPST01Paper110.pdf

[2] A. Gaouda, A. Chikhani, "Power quality detection and classification using wavelet-multiresolution signal decomposition" *IEEE Trans. Power Systems,* Vol. 14 4 , pp. 1469 – 1476, Oct 1.999. F.

[3] V. Vega, C. Duarte, G. Ordóñez "Detection and identification of power quality events using Discrete Wavelet Transform (DWT) and Artificial Neural Network" III Simposio Internacional sobre Calidad de la Energía Eléctrica SICEL 2005 Bogotá D.C., Nov. 2005.

[4] M. Kezunovic, Y. Liao, "A Novel Software Implementation Concept for Power Quality Study", 2000.

[5] C. Chui, *"Wavelets: a mathematical tool for signal analysis"*, Philadelphia, SIAM, 1997, pp. 210.

[6] I. Daubechies, *"Ten Lectures on Wavelets"*, Philadelphia: SIAM. 1992. Pp. 357.

[7] NTC 5000, Norma Técnica Colombiana 5000: "Calidad de la potencia eléctrica. Definiciones y términos fundamentales", ICONTEC, 2002.

[8] R. Rodríguez, S. Contreras, "Classification of normal and pathological voices using Wavelet Transform" *X Simposio de Tratamiento de Señales, Imágenes y Visión Artificial*, Cali, Colombia, pp. 4. 09 2005.

[9] J. C. Rodríguez, J. J. Mora, H. R. Vargas , G. Ordoñez, G. Carrillo, "Fault location in distribution systems using Support Vector Machine" III Simposio Internacional sobre Calidad de la Energía Eléctrica SICEL 2005 Bogotá D.C., Nov. 2005.

[10] J. Cormane, V. Barrera, "*Prediction of harmonics current in load residential windows, by means of artificial neural models "* Degree thesis Universidad Industrial de Santander, Colombia, 2003, Pp 164.

[11] T. Kohonen *"Self-Organizing Maps"* 2nd ed. Springer-Verlag Berlin Heidelberg. 1997.

BIOGRAPHIES

Valdomiro Vega García. Electrical Engineer UIS, Master in Engineering (Candidate) UIS. Scholarship holder, Bucaramanga, Colombia. Student Member IEEE. Part-time Professor of Escuela de Ingenierías Eléctrica, Electrónica y Telecomunicaciones Universidad Industrial de Santander. GISEL researcher. Areas of Work: Signal processing and Power quality email: valdomirovega@ieee.org valdomirovega@hotmail.com.

César Antonio Duarte Gualdrón. Electrical Engineer UIS, Master in Electrical Power UIS, Bucaramanga, Colombia. Assistant Professor of Escuela de Ingenierías Eléctrica, Electrónica y Telecomunicaciones Universidad Industrial de Santander. GISEL researcher. Areas of Work: Signal processing, Power quality and education based on competences. E-mail: cedagua@uis.edu.co.

Gabriel Ordóñez Plata. Electrical Engineer, UIS, Bucaramanga, Colombia. Doctorate Industrial Engineer UPCO, Madrid, Spain. Titular Professor Escuela de Ingenierías Eléctrica, Electrónica y Telecomunicaciones Universidad Industrial de Santander. GISEL director. Areas of work: Signal processing, electrical measurements, Power quality, technological management and education based on competences. Email: gaby@uis.edu.co.