Classification of Signals with Voltage Disturbance by Means of Wavelet Transform and Intelligent Computational Techniques.

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Abstract: - This article presents a classification method regarding voltage disturbance for three-phase signals obtained from disturbances recorded data in electric power systems. The proposed method uses wavelet transform to obtain a characteristic vector for voltage phases a, b and c, and a probabilistic neural network is used for classification. The classified signals as presenting voltage disturbance will form a database, being then available for future analyses. The results obtained with the application of this proposed methodology to a real system are also presented.

Key-Words: - **P**ower system, power quality, wavelet transform, probabilistic neural network, multiresolution analysis.

1 Introduction

The analysis of occurrences in electric power systems is of fundamental importance for secure operation of the system, and to maintain quality of the electric energy supplied to the consumers. The electric power utilities use equipments called disturbance registers (DR) for monitoring and diagnose of problems in the electric and protection systems. Those disturbance registers are usually installed in the substations, communicating then with a computer where the data can be analyzed. In a general way, the disturbance registers seek to monitor the protection system performance and detect faults in equipments and transmission lines, which could generate waveforms registers with typical duration of some seconds.

The waveforms usually analyzed in the electric power utilities operation centers, are those generated by events that usually cause the opening of lines due to circuit-breakers operation commanded by the protection devices. However, a great amount of stored data that can contain important information on the behavior and the performance of the system is not analyzed.

One of the difficulties, perhaps the most crucial in dealing with data obtained from DR equipments, is that a large amount of recorded data is not due to faults or switching operation in the electric power system. In fact, the great majority of the recorded signals are due to spurious variation as noises and failures in equipments. In that way, it becomes necessary to make use of automatic procedures for the classification of the signals of interest among the available recorded signals.

The proposal of this work is to use the available data in electric power utilities control and operation centers, obtained from DR equipments, that present voltage disturbances. The objective is to obtain from the recorded signals, a database with three-phase voltage waveforms that contains only those signals that present significant information about the performance of the electric power system due to the disturbance occurrence, to which it can be applied procedures to quantify magnitude and duration of the events, and later on, to use analyses and evaluation methods that can supply information on the behavior and performance of the electric system. Those information can be useful in faults identification; parameters evolution tendencies that can bring the system to a critical state; equipment sensibility evaluation to system-variations; critical points identification that may facilitate the adoption of preventive or mitigating procedures; and faults propagation evaluation through the system, among others.

Signals classification problems may be composed by a sequence of the following steps: (i) extraction of relevant signal characteristics; (ii) selection and classification of these characteristics. Proposed recent papers in electric signals classification [1], [2], [3], [4] have been using wavelet transform as tool for signal characteristics extraction; those characteristics are used as input to pattern recognition and classification procedures, which are based on computational intelligence.

This work presents the use of the wavelet transform for obtaining characteristic vectors starting from the recorded data, which are used as input for a Probabilistic Neural Network (PNN), for signal classification. The proposed method was implemented in Matlab™, using the Daubechies wavelet, db4.

2 Proposed Procedure

Fig. 1 shows schematically the proposed procedure to obtain a new database, starting from the real time original stored waveforms that are available in the electric power utilities control and operation centers.

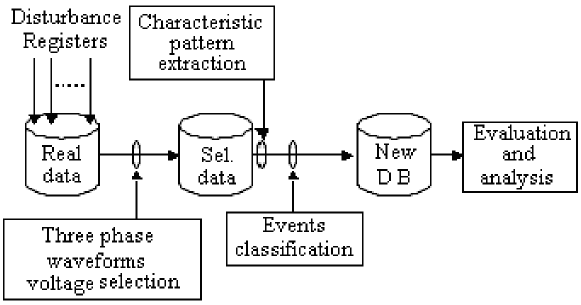

Fig. 1 - Proposed procedure scheme.

The real data contain the three-phase voltage and current waveforms, as well as digital signals indicating the relays and protection devices state, recorded by disturbance register in the electric system substations. From the original database, the voltage data for phases a, b and c, are selected, to which, wavelet transform is applied for characteristic vector extraction from each phase. These vectors are presented to a PNN for classification effect. The classified signals as presenting voltage disturbances form a new database containing those signals, already classified. From this new database a process of evaluation and analysis can be used to treat the stored data and obtain relevant information about the behavior of the electric system.

2.1 Wavelet Transform and multiresolution analysis

Wavelets are used to represent signals, in a similar way as Fourier analysis does with sine and cosine functions. The signal analysis through wavelet transform presents advantages on the traditional approach, using Fourier methods, when the analyzed signal presents discontinuity or transient response in time (non-stationary signals).

The Continuous Wavelet Transform (CWT) of a signal $f(t)$, depends on two variables: scale (or frequency), designated by the parameter a, and time (or position), designated by the parameter b, and it is given as:

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = \int_R f(t)\psi_{a,b}(t)dt \tag{1}$$

where the real function is defined as:

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

and the parameters a and b vary continually on R, the real set (with $a \neq 0$). The function ψ is called mother wavelet. The parameter b gives the position of the wavelet, while the parameter a is related with the resolution in frequency. For $|a| << 1$ the wavelet ψ is a highly compressed version, with high frequency content that corresponds to details contained in the signal that occur in a relatively short time. Consequently, for $|a| >> 1$, the wavelet ψ is very expanded, that is, a low frequency function, corresponding the global information in the signal.

In Discrete Wavelet Transform (DWT), the parameters a and b don't vary continually, and this way, they can only assume values in discrete steps. The DWT is obtained modifying to the wavelet representation for:

$$\psi_{m,n}(t) = 2^{\frac{-m}{2}} \psi(2^{-m}t - n) \tag{3}$$

where, $a = 2^m$ and $b = n2^m$ in (2).

The wavelet discretization process leads to the time-scale space representation in discrete intervals. The choice of the parameters a and b as powers of 2, leads to a dyadic sampling of the frequency and time axes. The parameter m is related with the frequency of the wavelet, while the parameter n indicates the position.

The Multiresolution Analysis (MRA), has the objective of representing a signal $f(t)$, in terms of an orthogonal base that is defined by the scale and wavelet functions. An efficient algorithm to produce this representation was developed by Mallat in 1988 [5]. The multiresolution analysis structure is shown in Fig. 2.

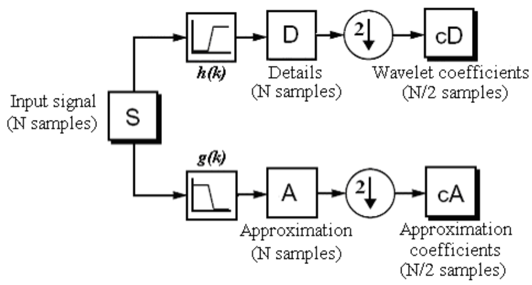

Fig. 2 - One stage MRA using convolution and decimation by factor 2.

The signal decomposition using wavelet transform can be seen as the original signal passing through two filters, a low-pass filter $g(k)$, called the scale function, and a high-pass filter $h(k)$, called the mother wavelet. The low-pass filter output represents the low frequency content of the input signal or an approximation of it. The high-pass filter output represents the high frequency content of the input signal or the details of this signal, which are represented by the signal cD, that contains the wavelet coefficients that are the new signal representation (the input signal representation in wavelet domain). The signal cA, which contains the approximation coefficients, is used to feed the next stage of the decomposition process obtaining, by an iterative procedure, multiple decomposition levels.

Fig. 3 shows an original signal containing a voltage sag (a), and the decomposition of this signal in six levels of details (b to g), and the last approximation in the sixth level (h).

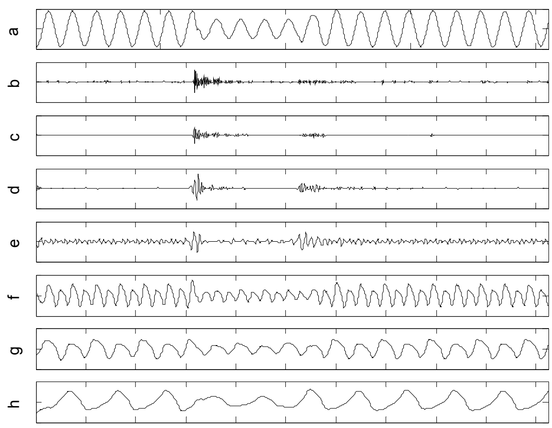

Fig. 3 Original signal with voltage sag (a), respective decomposition on six details (b-g) and one approximation (h).

2.2 Probabilistic Neural Network

A Probabilistic Neural Network (PNN) basically is a Bayesian classifier implemented in parallel. The PNN, as described by Specht [6], is based on the probability density function estimates for various classes established by the training patterns. A schematic diagram for a PNN is shown in Fig.4. The input layer is responsible for the connection of the input pattern X for the radial bases layer. $X = [x_1, x_2, \cdots, x_M]$, is a matrix containing the vectors to be classified.

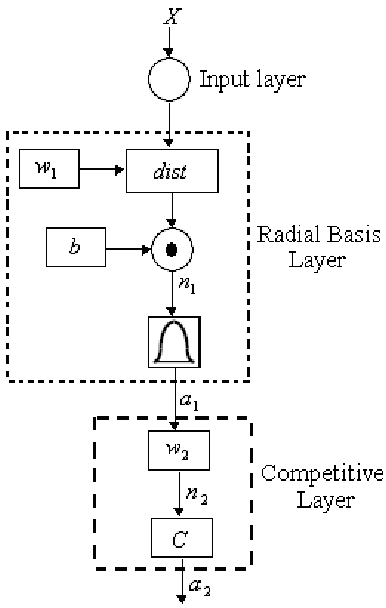

Figure 4. Probabilistic Neural Network architecture.

In the radial bases layer the training vectors are stored in a weight matrix w_1. When a new pattern is presented to the input, the *dist* block calculates the Euclidean distance from each input pattern vector to each weight vector stored. The output vector in *dist* block is multiplied, point-to-point, by a polarization factor, which defines the neuron sensibility, being

$$b = \sqrt{-\frac{\log 0.5}{\mu}} \qquad (4)$$

where μ is a user defined sensibility parameter, [8]. The result of that multiplication is n_1, that is applied to a radial base function supplying an output a_1 obtained through

$$a_1 = e^{-n_1^2} \quad (5)$$

Then, a vector in the input patterns close to a training vector is represented by a value close to 1 in the output vector a_1. In the competitive layer the weight matrix w_2 contains the target vectors representing each one of the classes corresponding to each vector in the training pattern. Each vector in w_2 has only an entry 1 in the row associated with that particular input class, and 0's elsewhere. The multiplication $w_2 a_1$ sums the elements of a_1 due to each of the input classes, supplying the output n_2. Finally, the C layer produces a_2, with an entry 1 corresponding to the largest element of n_2, and 0's elsewhere. Thus, the PNN network classifies the input vector into a specific class because that class has the maximum probability of being correct. The main advantage of PNN is its easy and direct project, and not depending of training

3 Application and results

The method uses the multiresolution decomposition that consists in time domain signal decomposition, in different resolution levels in the wavelet domain, to obtain a characteristic vector. Each one of the voltage signals in phases a, b, and c obtained from the recorded data is decomposed in 8 resolution levels together with a reference signal, without distortion. The characterization of the voltage disturbance is related with the contained energy in the several decomposition levels in the distorted signal compared with the pure waveform, by calculation of the norm, for each one of the levels. Then, a matrix with 3 vectors formed by differences involving the norms for each level of the reference signal and of the signal under analysis is obtained, corresponding each vector to one voltage signal phase. This matrix is used as input pattern for the PNN network for classification effects.

The proposed methodology is a general approach that may classify any voltage variation, ranging from fast transient variation as those related to lighting, and those slower ones related to faults, as voltage sags and voltage swells. As an example it will be presented signals that contain voltage sags in order to illustrate the application of the proposed methodology. The used PNN network is composed by 3 classes: class 1 – voltage sag; class 2 – voltage normal; class 3 – voltage swell. Two training vectors characterize each one of the classes; then, six training vectors are stored in the neural network. The training vectors were obtained through simulations.

For validation effect of the proposed method a group of 311 three phase voltage signals was used, obtained from recorded data in the utility ELETRONORTE operation center in Belém City - Brazil.

From the 311 three phase signals used for classification, 24 presented voltage sag, and the 287 remaining didn't present any voltage disturbance problem. These remaining 287 signals probably were recorded due to, spurious variation, noises, or other events. Fig. 5 and Fig. 6 show two signals, a normal one, without event occurrence, and an other with voltage sag in phase c, respectively. The signal of Fig. 5 was classified as 2 2 2, and the one of Fig. 6 as 2 2 1, being then both correctly classified.

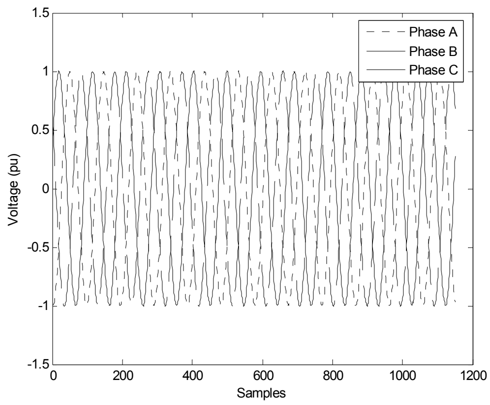

Fig. 5 - Three-phase signal without event occurrence. PNN output: 2 2 2.

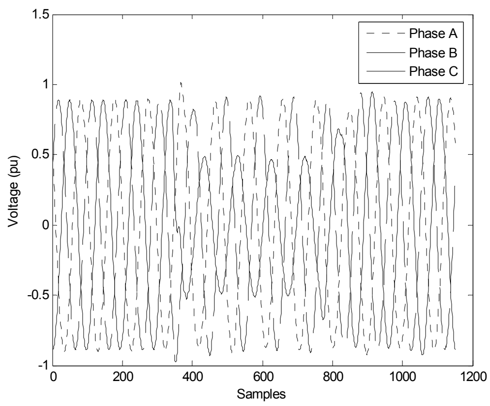

Fig. 6 - Three-phase signal with voltage sag in the phase c. PNN output: 2 2 1.

Table 1 shows the PNN output with corresponding classification for phases a, b, c respectively.

Table 1 – PNN output for the classified signals with voltage disturbamces, representing phases a b c.

Signal	PNN output	Signal	PNN output	Signal	PNN output
18	1 1 1	251	1 1 1	267	2 2 1
19	1 1 1	252	1 1 1	268	2 2 1
58	1 1 1	253	1 1 1	279	1 1 1
59	1 1 1	254	1 1 1	280	1 1 1
138	1 1 1	255	1 1 1	287	1 1 1
139	1 1 1	256	1 1 1	288	1 1 1
249	1 1 1	257	1 1 1	302	1 1 1
250	1 1 1	258	1 1 1	303	1 1 1

4 Conclusion

A voltage disturbance classification method in three phase signals was presented. The signals were obtained of recorded data by disturbances register in a real electric power system. The proposed method is based on wavelet transform for signal characteristic pattern extraction, and posterior classification using a probabilistic neural network. The classified signals as containing voltage disturbances can be quantified by the duration, frequency, and magnitude of the event. The quantification is accomplished using multiresolution signal analysis. The obtained results for the case of voltage sags (short duration voltage variation), that were used as an example validated the proposed methodology. The obtained modified data base containing only the voltage signals classified as relevant events may be used for evaluation and analysis of the electric system behavior.

References:

[1] Angrisani, L.; Daponte, P.; D'Apuzzo, M., *A method based on wavelet networks for the detection and classification of transients*, IEEE, Instrumentation and Measurement Technology Conference, 1998. IMTC/98. Conference Proceedings, Volume: 2, 18-21 May 1998, Page(s): 903-908.

[2] Santoso, S.; Powers, E.J.; Grady, W.M.; Parsons, A.C., *Power quality disturbance waveform recognition using wavelet-based neural classifier. I. Theoretical foundation*, IEEE, Transactions on Power Delivery, Volume: 15 Issue: 1, Jan. 2000, Page(s): 222-228.

[3] Santoso, S.; Powers, E.J.; Grady, W.M.; Parsons, A.C., *Power quality disturbance waveform recognition using wavelet-based neural classifier. II. Application*, IEEE, Transactions on Power Delivery, Volume: 15, Issue: 1, Jan. 2000 Pages:229 – 235.

[4] Huang, J.S.; Negnevitsky, M.; Nguyen, D.T., *A neural-fuzzy classifier for recognition of power quality disturbances,* IEEE, Transactions on Power Delivery, Volume: 17 Issue: 2 , April 2002, Page(s): 609-616.

[5] Mallat, S.G., *A theory for multiresolution signal decomposition: the wavelet representation*, IEEE, Transactions on Pattern Analysis and Machine Intelligence, Volume: 11 Issue: 7, July 1989 , Page(s): 674 -693.

[6] Specht, D.F., *Probabilistic neural networks for classification, mapping, or associative memory*, IEEE International Conference on Neural Networks, 1988, 24-27 July 1988 Page(s):525 - 532 vol.1.