Power Quality Event Identification Using Higher-Order Statistics and Neural Classifiers

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Abstract. This paper deals with power-quality (PQ) event detection, classification and characterization using higher-order sliding cumulants to examine the signals. Their maxima and minima are the main features, and the classification strategy is based in competitive layers. Concretely, we concentrate on the task of differentiating two types of transients (short duration and long duration). By measuring the fourth-order central cumulants' maxima and minima, we build the two-dimensional feature measured vector. Cumulants are calculated over high-pass digitally filtered signals, to avoid the low-frequency 50-Hz signal. We have observed that the minima and maxima measurements produce clusters in the feature space for 4th-order cumulants; third-order cumulants are not capable of differentiate these two very similar PQ events. The experience aims to set the foundations of an automatic procedure for PQ event detection.

1 Introduction

Power quality event detection and classification is gaining importance due to worldwide use of delicate electronic devices. Things like lightning, large switching loads, non-linear load stresses, inadequate or incorrect wiring and grounding or accidents involving electric lines, can create problems to sensitive equipment, if it is designed to operate within narrow voltage limits, or if it does not incorporate the capability of filtering fluctuations in the electrical supply [1,2].

The solution for a PQ problem implies the acquisition and monitoring of long data records from the energy distribution system, along with an automated detection and classification strategy which allows to identify the cause of these voltage anomalies. Signal processing tools have been widely used for this purpose, and are mainly based in spectral analysis and wavelet transforms. These second-order methods, the most familiar to the scientific community, are based

F. Sandoval et al. (Eds.): IWANN 2007, LNCS 4507, pp. 47–54, 2007.

on the independence of the spectral components and evolution of the spectrum in the time domain. Another tools are thresholding, linear classifiers and Bayesian networks. The goal of the signal processing analysis is to get a feature vector from the data record under study, which constitute the input to the computational intelligence modulus, which has the task of classification.

Some recent works bring a different strategy, based in higher-order statistics (HOS), in dealing with the analysis of transients within PQ analysis [2] and other fields of Science [3,4,5]. Without perturbation, the 50-Hz of the voltage waveform exhibits a Gaussian behavior. Deviations from Gaussianity can be detected and characterized via HOS. Non-Gaussian processes need third and fourth order statistical characterization in order to be recognized. In order words, second order moments and cumulants could be not capable of differentiate non-Gaussian events.

The situation described matches the problem of differentiating between a transient of long duration named fault (within a signal period), and a short duration transient (25 per cent of a cycle). This one could also bring the 50-Hz voltage to zero instantly and, generally affects the sinusoid dramatically. By the contrary, the long-duration transient could be considered as a modulating signal (the 50-Hz signal is the carrier). These transients are intrinsically non-stationary, so it is necessary a battery a observations (sample registers) to obtain a reliable characterization.

The main contribution of this work consists of the application of higher-order central cumulants to characterize PQ events (could be see as a complement of [2]), along with the use of a competitive layer as the classification tool. Results reveal that two different clusters, associated to both types of transients, can be recognized in the 2D graph. The successful results convey the idea that the physical underlying processes associated to the analyzed transients, generate different types of deviations from the typical effects that the noise cause in the 50-Hz sinusoid voltage waveform.

The paper is organized as follows: Section 2 summarizes the main equations of the cumulants used in the paper. Section 3 recalls the competitive layer's foundations, along with the *Kohonen* learning rule. The experience is described in Section 4, and the conclusions are drawn in Section 5.

2 Higher-Order Cumulants

High-order statistics, known as cumulants, are used to infer new properties about the data of non-Gaussian processes [6,7,8]. The relationship among the cumulants of r stochastic signals, $\{x_i\}_{i\in[1,r]}$, and their moments of order $p, p \leq r$, can be calculated by using the *Leonov-Shiryayev* formula [6,7,9,10]:

$$\begin{aligned} Cum(x_1, ..., x_r) = \sum (-1)^k \cdot (k-1)! \cdot E\{\prod_{i\in v_1} x_i\} \\ \cdot E\{\prod_{j\in v_2} x_j\} \cdots E\{\prod_{k\in v_p} x_k\}, \end{aligned} \quad (1)$$

where the addition operator is extended over all the set of v_i $(1 \leq i \leq p \leq r)$ and v_i compose a partition of *1,. . . ,r*.

Let $\{x(t)\}$ be an rth-order stationary random process. The rth-order cumulant is defined as the joint rth-order cumulant of the random variables $x(t)$, $x(t+\tau_1)$,. . . , $x(t+\tau_{r-1})$,

$$C_{r,x}(\tau_1, \tau_2, \ldots, \tau_{r-1}) \\ = Cum[x(t), x(t+\tau_1), \ldots, x(t+\tau_{r-1})]. \tag{2}$$

Considering $\tau_1 = \tau_2 = \tau_3 = 0$ in Eq. (2), we have some particular cases:

$$\gamma_{2,x} = E\{x^2(t)\} = C_{2,x}(0) \tag{3a}$$

$$\gamma_{3,x} = E\{x^3(t)\} = C_{3,x}(0,0) \tag{3b}$$

$$\gamma_{4,x} = E\{x^4(t)\} - 3(\gamma_{2,x})^2 = C_{4,x}(0,0,0) \tag{3c}$$

Equations (3) are measurements of the variance, skewness and kurtosis of the distribution in terms of cumulants at zero lags (the central cumulants). Normalized kurtosis and skewness are defined as $\gamma_{4,x}/(\gamma_{2,x})^2$ and $\gamma_{3,x}/(\gamma_{2,x})^{3/2}$, respectively. We will use and refer to normalized quantities because they are shift and scale invariant.

3 Competitive Layers: A Brief Summary

The neurons in a competitive layer distribute themselves to recognize frequently presented input vectors. The competitive transfer function accepts a net input vector **p** for a layer (each neuron competes to respond to **p**) and returns neuron outputs of 0 for all neurons except for the winner, the one associated with the most positive element of net input. If all biases are 0, then the neuron whose weight vector is closest to the input vector has the least negative net input and, therefore, wins the competition to output a 1.

The winning neuron will move closer to the input, after this has been presented. The weights of the winning neuron are adjusted with the *Kohonen* learning rule. Supposing that the ith-neuron wins, the elements of the ith-row of the input weight matrix (**IW**) are adjusted as shown in Eq. (4):

$$\mathbf{IW}_i^{1,1}(q) = \mathbf{IW}_i^{1,1}(q-1) + \alpha\left[\mathbf{p}(q) - \mathbf{IW}_i^{1,1}(q-1)\right], \tag{4}$$

where $\mathbf{p}$ is the input vector, q is the time instant, and α is the learning rate parameter. The *Kohonen* rule allows the weights of a neuron to learn an input vector, so it is useful in recognition applications. Thus, the neuron whose weight vector was closest to the input vector is updated to be even closer. The result is that the winning neuron is more likely to win the competition the next time a similar vector is presented. As more and more inputs are presented, each neuron in the layer closest to a group of input vectors soon adjusts its weight vector toward those inputs. Eventually, if there are enough neurons, every cluster of similar input vectors will have a neuron that outputs 1 when a vector in the cluster is presented, while outputting a 0 at all other times. Thus, the competitive network learns to categorize the input vectors it sees.

4 Experimental Results

The aim is to differentiate between two classes of transients (PQ events), named long-duration and short-duration. The experiment comprises two stages. The feature extraction (classification) stage is based on the computation of cumulants. Each vector's coordinate corresponds to the local maximum and minimum of the 4th-order central cumulant. And the classification stage is based on the application of the competitive layer to the feature vectors, in order to obtain two clusters in the feature plane. We use a two-neuron competitive layer, which receives two-dimensional input feature vectors in this training stage.

We analyze a number of 16 1000-point (roughly) real-life registers during the feature extraction stage. Before the computation of the cumulants, two preprocessing actions have been performed over the sample signals. First, they have been normalized because they exhibit very different-in-magnitude voltage levels. Secondly, a high-pass digital filter (5th-order Butterworth model with a characteristic frequency of 150 Hz) eliminates the low frequency components which are not the targets of the experiment. This by the way increases the non-Gaussian characteristics of the signals, which in fact are reflected in the higher order cumulants.

After filtering, a 50-point sliding battery of central cumulants (2nd, 3rd and 4th order) are calculated. The window's width (50 points) has been selected neither to be so long to cover the whole signal nor to be very short. The algorithm calculates the 3 central cumulants over 500 points, and then it jumps to the following starting point; as a consequence we have 98 per cent overlapping sliding windows (49/50=0.98). Thus, each computation over a window (called a segment) outputs 3 cumulants.

Fig. 4 and Fig. 2 show an example of signal processing analysis of two sample registers corresponding to a long-duration and a short-duration events, respectively.

The second-order cumulant sequence corresponds to the variance, which clearly indicates the presence of an event. Both types of transients exhibit an increasing variance in the neighborhood of the PQ event, that presents the same shape, with only one maximum. The magnitude of this maximum is by the way the only available feature which can be used to distinguish different events from the second order point of view. This may suggest the use of additional features in order to distinguish different types of events.

For this reason the higher-order central cumulants are calculated. An unbiased estimator of the cumulants have been selected. Third-order diagrams don't show quite different clusters if we consider a bi-dimensional space (2 coordinates

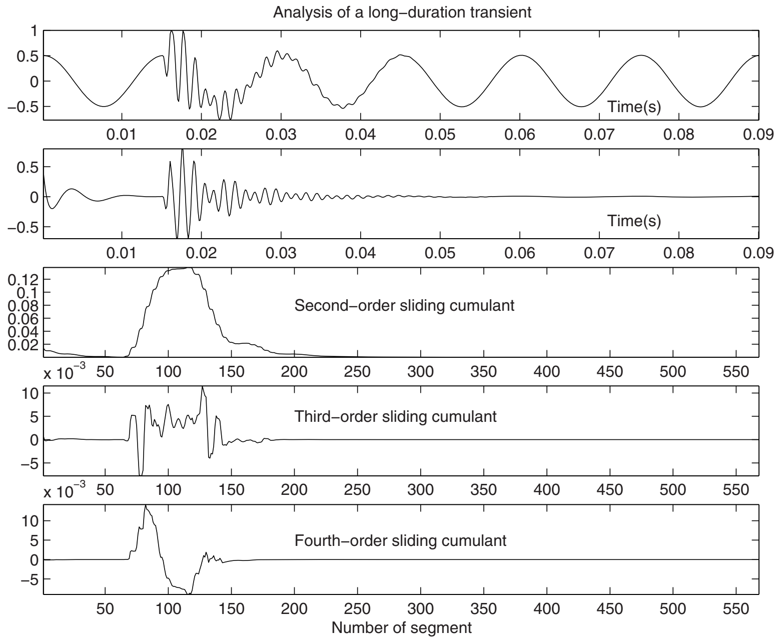

Fig. 1. Long duration transient analysis. From top to bottom: the original data record, the filtered sequence, 2nd-3rd-4th-order central cumulants sliding windows, respectively.

for each feature vector) because maxima and minima are similar. It is possible to differentiate PQ events from the 3rd-order perspective if we consider more features in the input vector, like the number of extremes (maxima and minima), and the order in which the maxima and the minima appear as time increases. In this paper we have focussed the experience on a bi-dimensional representation (2-dimensional feature vectors) because we obtain very intelligible 2-D graphs.

Fourth-order sliding cumulants exhibit clear differences, not only for the shape of the computation graph (the bottom graph in Figs. 2 and 4), but also for the different location of minima, which suggest a clustering for the points.

Fig. 3 presents the results of the training stage, using the *Kohonen* rule. The horizontal (vertical) axis corresponds to the maxima (minima) value. Each cross in the diagram corresponds to an input vector and the circles indicate the final location of the weight vector (after learning) for the two neurons of the competitive layer. Both weight vectors point to the asterisk, which is the initializing point (the midpoint of the input intervals).

The separation between classes (inter-class distance) is well defined. Both types of PQ events are horizontally clustered. The correct configuration of the clusters is corroborated during the simulation of the neural network, in which we have obtained an approximate classification accuracy of 97 percent. During the simulation new signals (randomly selected from our data base) were processed using the method described.

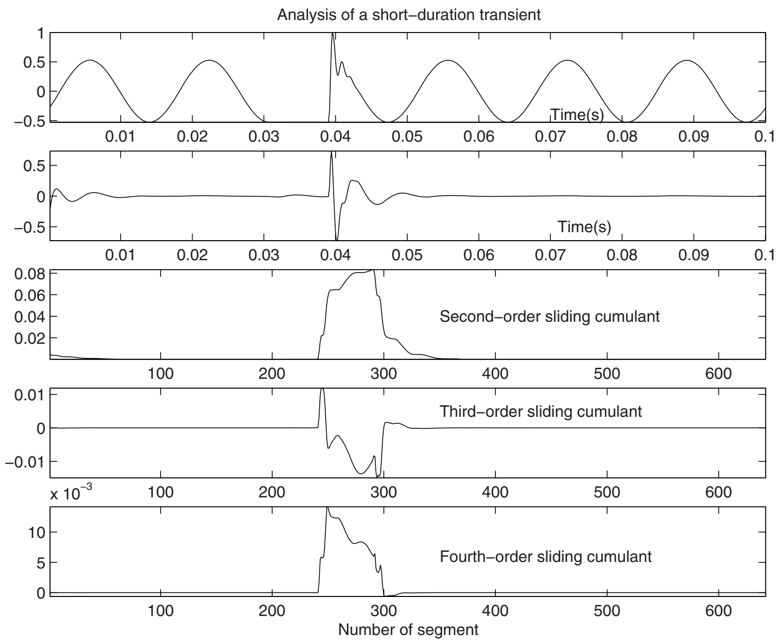

Fig. 2. Short duration transient analysis

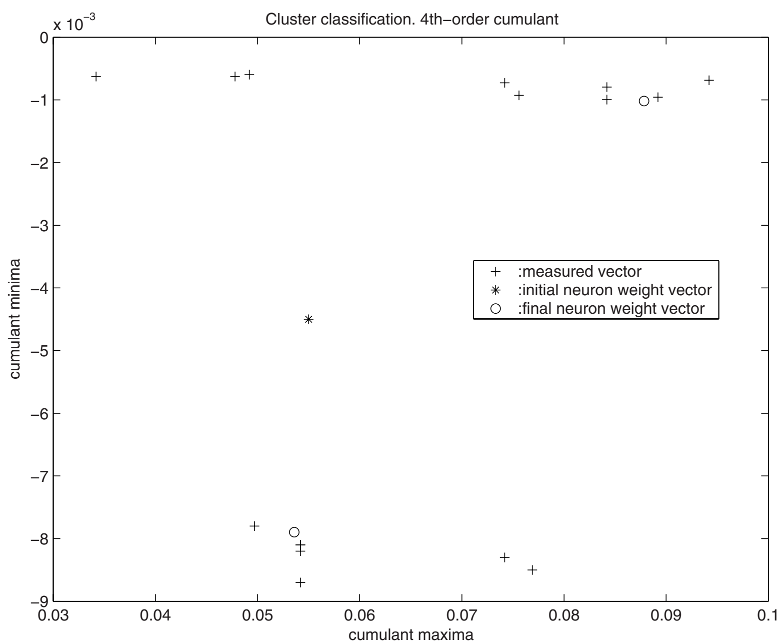

Fig. 3. Competitive layer training results over 20 epochs

The accuracy of the classification method increases with the number of data. To evaluate the confidence of the statistics a significance test have been conducted. This informs if the number of experiments is statistically significant according to the fitness test [2]. As a result of the test, the number of measurements is significatively correct.

5 Conclusion

In this paper we have proposed a method to detect and classify two PQ transients, named short and long-duration. The method comprises two stages. The first includes pre-processing (normalizing and filtering) and outputs the 2-D feature vectors, each of which coordinate corresponds to the maximum and minimum of the central cumulants. The second stage uses a neural network to classify the signals into two clusters. This stage is different-in-nature from the one used in [2] consisting of quadratic classifiers. The configuration of the clusters is assessed during the simulation of the neural network, in which we have obtained an acceptable classification accuracy.

Acknowledgement

The authors would like to thank the *Spanish Ministry of Education and Science* for funding the project DPI2003-00878 which involves noise processes modeling. Also thanks to the *Andalusian Government* for the trust they put in the research unit TIC-168 and the project TIC-155.

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