HOS-BASED METHOD FOR POWER QUALITY EVENT CLASSIFICATION

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ABSTRACT

This paper presents a novel method for classification of power quality events in voltage signals which makes use of higher order statistics based technique for extracting a reduced and representative event signature vector. The signature vectors composed of samples from the diagonal slices of the second and forth order cummulants, which are selected with Fisher's discriminant ratio (FDR), provide enough separability among classification regions resulting in classification rate as high as 100% if the voltage signals are corrupted by the presence of isolated events. A comparison performance among the proposed method and two other ones found on the literature is provided and reveals that the proposed method not only achieve a good performance, but it also surpass the performance of previous techniques.

1. INTRODUCTION

Power Quality (PQ) can be viewed as the normal operation of the power system in terms of its nominal voltage signal waveform [1]. Following this definition, the main PQ events are transients, long and short voltage variations, flickers, harmonics, unbalances, etc [2, 3]. The PQ analysis is a research field of increasing demanding attention in the recent few years, among the several reasons for that are: 1) the fast expansion use of power electronics devices leads to a wide diffusion of nonlinear, time-variants loads in the power system, which causes several power quality problems; 2) the growing use of accurate electronic devices requiring high quality power supplies; 3) the need to localize the disturbance sources envisaging to quickly solve the power quality problem; 4) the large amount of power quality data recorded that demands automatic classification.

The digital signal processing techniques are been largely employed on PQ analysis for event detection and classification, pollution source identification and localization, parameters estimation, etc.

This work focuses on the PQ events classification and propose the use of a higher-order statistics-based (HOS) technique, such as cummulants, applied over the voltage waveform for feature extraction. It appears to be interesting the use of cummulants because they are not sensitive to background Gaussian noise and they are also useful in problems where either non-Gaussianity or nonlinearities are important [4, 5]. The classification is performed with an artificial neural network.

For classification of waveform disturbance in voltage signals, several works have been introduced so far. Among them, the recently developed methods proposed in [6, 7, 8, 9, 10] shown good results. In general, these methods make use of feature extraction techniques followed by traditional pattern recognition techniques. The wavelet transforms are been widely employed for feature extraction [6, 7, 8, 9, 10] and for pattern recognition the artificial neural networks [11, 12], fuzzy logic [13, 14], genetic algorithms [15] and support vector machines [16] are been used.

In this paper, the proposed method for PQ event classification is presented and a comparison with two other methods [6, 7] and [12] is performed. The main advantages of the proposed method are the non sensibility to Gaussian background noise and it leads to a simplification on the classification algorithm and a performance improvement.

2. PQ EVENT CLASSIFICATION PROBLEM

A designed system for power quality event classification should be able to correct recognize the occurrence of each abnormal condition on the discrete version of the voltage signal of the power system ($x(n)$), which can be expressed as an additive contribution of several types of phenomena

$$x(n) = x(t)|_{t=nT_s} := f(n) + h(n) + i(n) + t(n) + v(n) \quad (1)$$

where $n = 0, \cdots, N-1$, $T_s = \frac{1}{f_s}$ is the sampling period, the sequences $\{f(n)\}$, $\{h(n)\}$, $\{i(n)\}$, $\{t(n)\}$ e $\{v(n)\}$ represent the power supply fundamental component, harmonics, inter-harmonics, transient, and background noise, respectively. Each of these signals is defined as follows:

$$f(n) := A_0(n)\cos(2\pi\frac{f_0(n)}{f_s}n + \theta_0(n)), \quad (2)$$

$$h(n) := \sum_{m=1}^{M} h_m(n), \quad (3)$$

$$i(n) := \sum_{j=1}^{J} i_j(n), \quad (4)$$

$$t(n) := \sum_{k=1}^{K} t_k(n), \quad (5)$$

and $\{v(n)\}$ is independent, identically distributed (i.i.d.) noise, and Normal $\mathcal{N}(0, \sigma_v^2)$.

In (2), $A_0(n)$, $f_0(n)$ e $\theta_0(n)$ are the magnitude, fundamental frequency, and phase of the power supply signal, respectively. In (3) and (4), $h_m(n)$ is the m-th harmonic and $i_j(n)$ is the j-th inter-harmonic, which are defined as

$$h_m(n) := A_m(n)\cos(2\pi m\frac{f_0(n)}{f_s}n + \theta_m(n)), \quad (6)$$

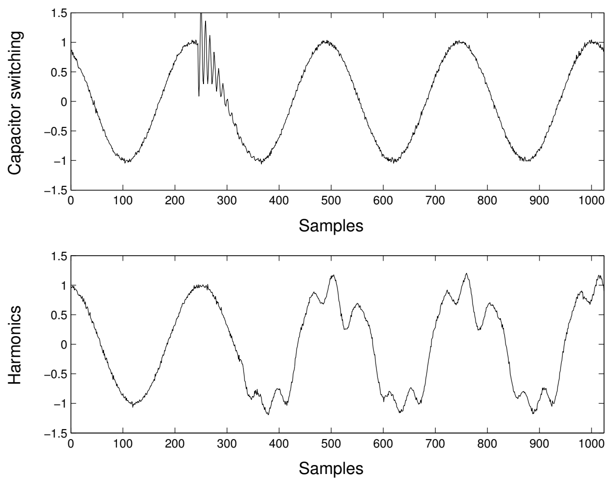

Figure 1: Example of events named capacitor switching and harmonic.

and

$$i_j(n) := A_{I,j}(n)\cos(2\pi\frac{f_{I,j}(n)}{f_s}n + \theta_{I,j}(n)). \quad (7)$$

In (6), $A_m(n)$ is the magnitude and $\theta_m(n)$ is the phase of the m-th harmonic. In (7), $A_{I,j}(n)$, $f_{I,j}(n)$, and $\theta_{I,j}(n)$ are the magnitude, frequency, and phase of the j-th inter-harmonic, respectively. $\{t_k(n)\}$ in (5) is the k-th transient signal such as spikes, notches, capacitor switchings, etc.

The normal operation of the power system can be modeled as

$$\begin{aligned} x_n(n) = f(n) + v(n) = \\ A_0(n)\cos(2\pi\tfrac{f_0(n)}{f_s}n + \theta_0(n)) + v(n), \end{aligned} \quad (8)$$

and an event occurs when some abnormal condition pollute the voltage waveform such as a capacitor switching $x_c(n)$, modeled by Eq. (9) or a harmonic event $x_h(n)$, modeled by Eq. (10) as depicted in Fig. 1.

$$x_c(n) = A_0(n)\cos(2\pi\frac{f_0(n)}{f_s}n + \theta_0(n)) + t(n) + v(n) \quad (9)$$

$$x_h(n) = A_0(n)\cos(2\pi\frac{f_0(n)}{f_s}n + \theta_0(n)) + h(n) + v(n) \quad (10)$$

3. PROPOSED SYSTEM FOR PQ EVENT CLASSIFICATION

The block diagram of the proposed method and so-called HOS-based method for power quality event classification is portrayted in Fig. 2. Note that the feature extraction is performed over the voltage waveform of the PQ event and the classification is performed over the selected features.

In this work, a HOS-based technique is used for feature extraction, where the diagonal slices of second, third and forth order cummulants are extracted from the voltage waveform. To reduce the dimension of the extracted features and consequently the computational complexity and processing time, the Fisher's discriminant ratio (FDR) [17] is used, aiming at the choice of a representative and finite set of features among those obtained by HOS that provides a good separability between two distinct classes.

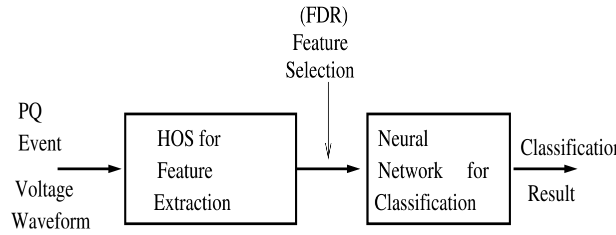

Figure 2: Proposed system for power quality event classification

Finally, the selected samples from the cummulants are presented to an artificial neural network for the classification purpose.

3.1 Higher-Order Statistics

It has been shown so far that higher-order statistics-based techniques are more appropriate to deal with non Gaussian processes and nonlinear systems than the second-order ones. Remarkable results regarding detection, classification and system identification with cummulant-based method have been reported in [18], [4], [19] and [5]. Assuming that voltage signals are modeled as a non Gaussian process, the use of cummulant-based method appears to be a very promising approach for detection of abnormal behaviors in voltage signals. In fact, HOS-based signature vectors of voltage events provide that each class of voltage events, which is defined as a classification region related to the class ω_i, $i = 1, \ldots, C$ in a hyperspace expanded by the signature vectors, is very well defined. The expressions of the diagonal slice of second, third, and fourth order cummulants of a zero mean $x(n)$ are respectively expressed by

$$C_{2,x}(i) = E\{x(n)x(n+i)\}, \quad (11)$$

$$C_{3,x}(i) = E\{x(n)x^2(n+i)\} \quad (12)$$

and

$$C_{4,x}(i) = E\{x(n)x^3(n+i)\} - 3C_{2,x}(i)C_{2,x}(0), \quad (13)$$

respectively, where i is the i-th delay. Considering $\mathbf{x}(n)$ as a finite-length vector and $i = 0, 1, 2, \cdots, N-1$, approximations of such cummulants are here defined by

$$\hat{C}_{2,x}(i) = \frac{1}{N}\sum_{n=0}^{N-1} x(n)x\left(\mathrm{mod}(n+i,N)\right), \quad (14)$$

$$\hat{C}_{3,x}(i) = \frac{1}{N}\sum_{n=0}^{N-1} x(n)x^2\left(\mathrm{mod}(n+i,N)\right), \quad (15)$$

and

$$\begin{aligned} \hat{C}_{4,x}(i) = \tfrac{1}{N}\sum_{n=0}^{N-1} x(n)x^3\left(\mathrm{mod}(n+i,N)\right) - \\ 3\tfrac{1}{N^2}\sum_{n=0}^{N-1} x(n)x\left(\mathrm{mod}(n+i,N)\right)\sum_{n=0}^{N-1} x^2(n) \end{aligned}, \quad (16)$$

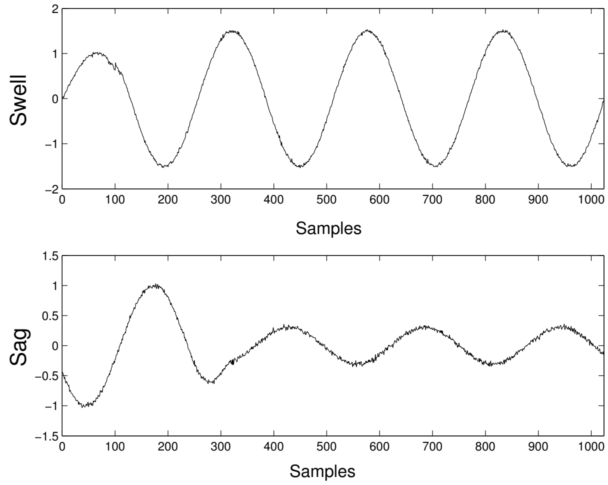

Figure 3: Examples of disturbances named swell and sag.

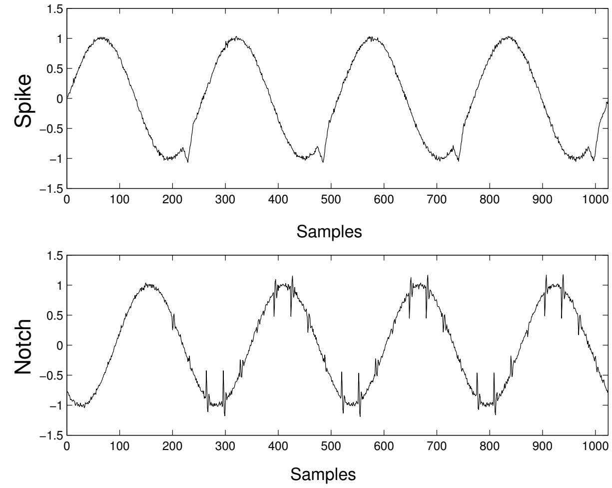

Figure 4: Example of disturbances named spike and notch.

where the function $\mathrm{mod}(a,b)$ is the modulus, returning the integer remainder after dividing a into b. The approximations presented in (14)-(16) lead to a very appealing approach for problems where we have a finite-length vector from which features have to be extracted for applications such as detection, classification, and identification.

Once the cummulants have been extracted, they should be normalized and a feature selection method is performed.

3.2 Feature Selection

Aiming at the choice of a representative and finite set of features among those obtained by HOS that provides a good separability between two distinct events, the use of the FDR is applied [17]. The cost vector function of the FDR which leads to a best separability in a low-dimensional space between both aforementioned events is given by

$$\mathbf{J}_c = \left(\mathbf{m}_1 - \mathbf{m}_2\right)^2 \odot \frac{1}{\mathbf{D}_1^2 + \mathbf{D}_2^2} \tag{17}$$

where $\mathbf{J}_c = [J_1 \cdots J_{L_l}]^T$, L_l is the total number of features, $\mathbf{m}_1$ and $\mathbf{m}_2$, and $\mathbf{D}_1^2$ and $\mathbf{D}_2^2$ are the mean and variance of the features vectors $\mathbf{p}_{1,k}$, $k = 1,2,\cdots,M_p$ and $\mathbf{p}_{2,k}$, $k = 1,2,\cdots,M_p$, when $\mathbf{x}(n)$ assumes to be one abnormal condition such as a spike and another abnormal condition such as a notch, respectively, and M_p denotes the total number of feature vectors (number of events used for the feature selection). $\odot$ refers to the Hadamard product $\mathbf{r} \odot \mathbf{s} = \left[r_0 s_0 \cdots r_{L_r-1} s_{L_r-1}\right]^T$.

From (17), it is understandable that the i-th element of the feature vector providing the greater values of J_i are selected for use in the classification.

It is important to stress that the feature selection is performed offline, therefore, during the system design only the selected features are used for event classification.

3.3 Event Classification

The use of the FDR leads to the selection of a set of cummulant that provides the best class separation in according to the FDR criterion. Therefore, it is possible to reduce the dimension of the data presented to the classifier to simplify the classification algorithm.

A multilayer feed-forward neural network is used for event classification due to the good performance achieved for nonlinear pattern recognition [20] and the low computational cost when comparing with others non-linear classifiers as the kernel support vectors machines (SVM) [21].

4. METHODOLOGY

In this work, six classes of PQ events are considered: harmonics (C1), sags (C2), swells (C3), capacitor switching (C4), notches (C5) and spikes (C6). The events were simulated by software following the definitions found in [2, 3] and [19] with a sampling frequency (f_s) of 15360 samples per second and with a total length (N) of 1024 samples. Five hundred events were generated per class and were equally divided in two groups, one for the system design and the other for system validation ($M_p = 250$ in Section 3.2). All events were generated with an additive Gaussian white noise with a signal to noise ratio (SNR) of 30 dB.

The sags and swells (see Fig. 3) were arranged in one class because the separability between them is straight forward using one information from the event detector algorithm [22], which is not described here because it is not the focus of this work. Figure 4 shows a spike and a notch event while a harmonic and a capacitor switching can be seen in Fig. 1.

4.1 System Design

The first step to design the system is to compute the diagonal slices of the second, third and forth order cummulants for the N samples of each event according to Equations (14), (15) and (16), respectively. Therefore, for each event, a total of $3 \times N$ samples from the three cummulants for each event are obtained. The resultant vector, with the cummulants for the selected event, is divided by the first sample of the diagonal slice of the second order cummulant ($\hat{C}_{2,x}(0)$) for normalization.

Aiming at reducing the dimension of the data presented to classifier and also to select the most representative set of parameters envisaging good separability between classes,

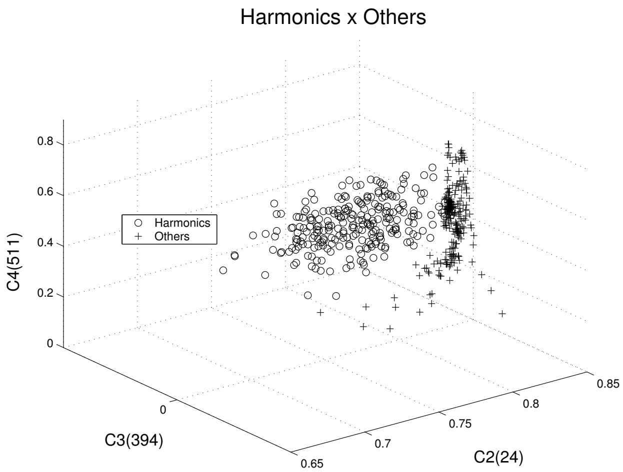

Figure 5: Example of the separability between harmonics and the other classes using the selected parameters from the diagonal slice of cummulants. C2 from the second order, C3 from the third order and C4 from the fourth order cummulant.

the FDR is applied on the normalized cummulants using Eq. (17). The FDR was computed considering one class against the others, therefore, for each class a vector $\mathbf{J}_c$ with $3 \times N$ elements is obtained. Taking the greater value of $\mathbf{J}_c$ related to each cummulant, a total of 3 parameters for each class are selected, given a total of 15 parameters for each event. Therefore, the original dimension of each event was reduced from 1024 samples to 15 samples. This procedure is performed offline. As an example, Figure 5 shows the three selected parameters from each cummulant for harmonic events (o) and for the other events (+), showing the separability between these two sets.

The 15 selected parameters are finally presented to a multilayer feed-forward neural network for event classification. During the system design, the neural network is trained using the back-propagation algorithm and the training process is stopped when the desired classification performance is achieved.

Analyzing the neural network training procedure, it was verified that the achieved performance on the event classification improves using only the samples related to the cummulants of second and forth order. Therefore, a further reduction on the classifier input vector dimension was achieved, from 15 to 10 parameters.

A closer look on the third order cummulant reveals that the amount of energy related to this cummulant is much smaller than the energy of the second (40 times greater) and forth (22 times greater) order cummulants. Therefore, it is understandable why the third order cummulant doesn't help the classification algorithm. The energy (E_{C_k}) was measured according to Equation (18),

$$E_{C_k} = \sqrt{\sum_{i=1}^{N} \frac{C_k(i)^2}{N}} \tag{18}$$

where $C_k(i)$ is the k-th order cummulant and $N = 1024$ is the total number of samples.

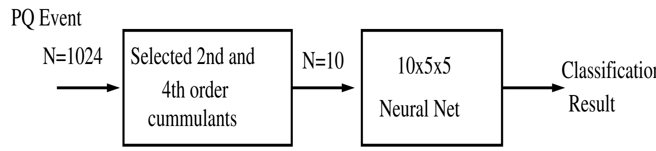

Figure 6: Implemented System

4.2 Implemented System

The implemented system can be seen in Fig. 6. First, the selected samples of the second and forth order cummulants of the detected PQ event with length $N = 1024$ ($f_s = 15360$ Samples/s) are computed and normalized by $\hat{C}_{2,x}(0)$, resulting into a new vector with length $N = 10$. This new vector feeds the previously trained neural network with 3 layers, the input layer with 10 input nodes, the hidden layer with 5 neurons and the output layer also with 5 neurons (5 classes). The highest value indicates the event class at the neural network output.

5. SYSTEM VALIDATION RESULTS

In order to evaluate the performance of the proposed system, the validation set of power quality events were used. A comparison between the proposed method and the OTFR [6, 7] and the LCEC [12] is also performed. The main motivation for choosing these methods resides on the fact that both show remarkable results when applied to waveform disturbance classification of voltage signals.

Table 1 shows the achieved results for the three methods. The HOS method shows a remarkable result in terms of performance and a reasonable computational complexity as shown in Tab. 2, in comparison with the other two methods.

Table 1: Classification rate and overall efficiency in % offered by LCEC, OTFR-based and the HOS-based method.

PQ Event	LCEC	OTFR	**HOS**
C1	95.50	100.00	**100.00**
C2	99.50	100.00	**100.00**
C3	99.50	100.00	**100.00**
C4	100.00	97.84	**100.00**
C5	99.50	95.23	**100.00**
C6	99.00	99.69	**100.00**
Overall Efficiency	93.13	92.88	**100.00**

Table 2: Computational complexity of LCEC, OTFR-based and HOS-based methods for the simulation results.

Operation	LCEC	OTFR	**HOS**
Sum	6289	86373	**23637**
Multiplication	1793	108022	**38004**
tanh(.)	23	70	**10**

6. CONCLUSIONS

In this paper, a novel method for power quality event classification based on higher order statistics for feature extraction is presented. The use of the diagonal slices of the second and forth order cummulants together with the Fisher's discriminant ratio for feature selection leaded to a small number of parameters to be used for the classification purpose.

An artificial neural network was used for classification and the simulation results shown a remarkable performance of the proposed method. The overall performance for the 6 considered classes was 100% for the validation events set.

A comparison with other two methods shown that the proposed method achieved the best performance. However, it worth to point out that the LCEC is the one requiring the lowest computational cost.

The OTFR method shown high performance for narrow-band events such as sags, swell and harmonics, but the performance decreases for the other disturbances.

A noise study of the proposed method is planned to be performed, but good results are expected as the fourth order cummulant is blind to Gaussian noise although the second order cummulant is affected.

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