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# Exploiting Higher-Order Statistics Information for Power Quality Monitoring

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## 1. Introduction

The basic requirement for a Power Quality (PQ) monitoring system is the automatic detection of the PQ disturbances. Furthermore, the monitoring system should be capable of distinguishing different classes of disturbances. Usually, the PQ disturbance detection and classification tasks are performed in the power system voltage signal, because the majority of disturbances are mainly related to changes in the voltage signal. As a result, disturbance detection and classification in voltage signals can, indeed, assist the identification of the underlying source of disturbances. Disturbances that often appear in the power system voltage signals comprise sags, swells, outages, harmonics, oscillatory transients, notching and spikes, causing failure or miss-operation of the electrical equipments (Morsi & El-Hawary, 2008). Several authors use the denomination of waveform distortion for periodic distortion added to the voltage signal, such as harmonic distortion, notchings, etc. In this work we will use the term disturbance indistinctly for both periodic or non periodic distortions.

In order to improve PQ, the underlying sources and causes of such disturbances must be known before appropriate actions be taken. However, for determining the causes and sources of disturbances, one must have, *a priori*, the ability to automatic detect and classify such disturbances. In the last two decades, researchers have attempted to use appropriate signal processing and computational intelligence techniques for that aim. A good review about the main signal processing tools applied to the PQ problem can be found in Bollen et al. (2009).

In general, a detection and/or classification system comprises processing blocks as shown in Figure 1. The preprocessing step can be viewed as the application of signal decomposition techniques (de Aguiar et al., 2009; Ferreira, de Seixas & Cerqueira, 2009; Gaouda et al., 1999), aiming at expliciting the primitive components of the electric signals, and signal segmentation (Bollen et al., 2009; Styvaktakis et al., 2002), which envisage the data partition into frames with a fixed number of samples. The preprocessing can range from a simple signal processing technique up to more complex signal decomposition techniques as it is well discussed in Duda et al. (2000).

Feature extraction is an essential step towards a successful disturbance detection and classification. It is based on subjective knowledge gathered from power system specialists or objective information extracted from the voltage signal. Regarding objective information,

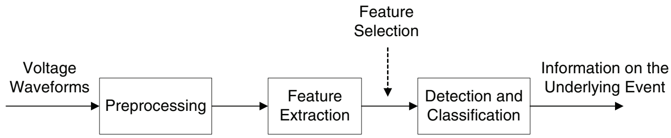


Fig. 1. Basic detection and classification system.

features can sometimes be extracted without considering the specific nature of voltage signals, for instance by using the outputs from signal transformations, which includes the Discrete Fourier Transform (DFT), Short Time Fourier Transform (STFT), wavelets, and other time-frequency signal decomposition methods, and/or using second-order statistics, Root Mean Square (RMS) values, etc (Bollen et al., 2009). Several works found in the literature have pointed out the Discrete Wavelet Transform (DWT) (Mallat, 1999) and S-Transform (ST) (Stockwell et al., 1996) are efficient feature extraction techniques for PQ disturbances, mainly due to their capability to represent the signal frequency components, preserving the time information (Mishra et al., 2008; Samantaray, 2010).
The main goal of the feature extraction, in both detection and classification contexts, is to represent the data set in a new feature space in which the probability to distinguish classes is higher than the one in the original space. Typically, feature selection techniques will result in low computational burden approaches for detection and/or classification of disturbances. Nevertheless, some important aspects must be considered for choosing the feature extraction tool for PQ monitoring. Among them, the following ones must be carefully taken into account:

1. The sensitivity to noise. The monitoring system performance can be strongly corrupted by the presence of noise in the electric signals;
2. The sensitivity to power frequency variations. A variation of 2% can be found in the nominal voltage frequency, and this variation can also reduce the performance of the monitoring system;
3. Computational burden. For real-time applications, low cost and complex techniques should be chosen.

The DWT is a very attractive tool, as a feature extraction technique for PQ disturbance detection and classification. However, difficulties may arise when the signals are corrupted by noise and/or when the number of samples of the signal window is reduced. In order to overcome these limitations, some recent works (Ferreira, Cerqueira, Duque & Ribeiro, 2009; Ribeiro et al., 2006; 2007) have been exploiting the usage of Higher-Order Statistics (HOS) (Mendel, 1991) as features for PQ monitoring. HOS measures are extensions of second-order measures (such as the autocorrelation function and power spectrum) to higher orders (Mendel, 1991). Any Gaussian signal is completely characterized by its mean and variance. Consequently, the HOS information for Gaussian signals is useless. However, many signals encountered in practice have non-zero mean HOS, and many measurement noises are Gaussian, and so, in principle, the HOS is less affected by Gaussian background noise than the second-order measures (Mendel, 1991). This is the main motivation for the usage of the HOS in voltage signals.
This chapter focuses on detection and classification of PQ disturbances based on HOS for feature extraction. Cumulants (Mendel, 1991) are extracted from the power system signals using a simple estimation for finite length vectors, as proposed in Ribeiro et al. (2006). Based on these features, a Bayesian detection system followed by a neural classifier are both

designed. Additionally, a filter bank is used envisaging multiple disturbance decoupling, in order to increase the performance of the neural classifier in presence of more complex disturbance contexts.
This chapter is organized as follows. Next section presents a model to describe the power signal in the presence of PQ disturbances. Section 3 discusses the main features of the HOS information. In Section 4, both preprocessing and feature extraction based on HOS for PQ are presented. Section 5 illustrates the power of HOS features for PQ automatic disturbance detection and classification and, the conclusions are derived in Section 6. Finally, future tends in PQ detection and classification issues are pointed out in Section 7.

## 2. PQ problem formulation

The discrete version of the monitored voltage signal can be segmented into non-overlapped frames of $N$ samples, which are expressed as an additive contribution of several types of phenomena, as previously formulated in Ribeiro & Pereira (2007):

$$v[n] = v(t)|_{t=\frac{n}{f_s}} = f[n] + h[n] + i[n] + t[n] + r[n] \tag{1}$$

where $n = 0, \cdots, N-1$, $f_s$ is the sampling frequency, the sequences $f[n]$, $h[n]$, $i[n]$, $t[n]$ and $r[n]$ are the fundamental component, harmonics, interharmonics, transient and background noise, respectively. Each of these signals is defined as follows:

$$f[n] = A_0[n]\cos[2\pi\frac{f_0[n]}{f_s}n + \theta_0[n]], \tag{2}$$

$$h[n] = \sum_{m=1}^{M} h_m[n], \tag{3}$$

$$i[n] = \sum_{j=1}^{J} i_j[n], \tag{4}$$

$$t[n] = t_{imp}[n] + t_{not}[n] + t_{osc}[n], \tag{5}$$

and $r[n]$ is independently and identically distributed (i.i.d.) normal noise $\mathcal{N}(0, \sigma_n^2)$ and independent of $f[n]$, $h[n]$, $i[n]$ and $t[n]$. In (2), $A_0[n]$, $f_0[n]$ and $\theta_0[n]$ refer to the magnitude, fundamental frequency, and phase of the fundamental component, respectively. In (3) and (4), $h_m[n]$ and $i_j[n]$ are the $m$th harmonic and the $j$th interharmonic, respectively, which are defined as:

$$h_m[n] = A_m[n]\cos[2\pi m\frac{f_0[n]}{f_s}n + \theta_m[n]][u[n - n_{h_{m,i}}] - u[n - n_{h_{m,f}}]], \tag{6}$$

and

$$i_j[n] = A_{I,j}[n]\cos[2\pi\frac{f_{I,j}[n]}{f_s}n + \theta_{I,j}[n]][u[n - n_{i_{j,i}}] - u[n - n_{i_{j,f}}]], \tag{7}$$

in which $u[n]$ denote the unit step sequence, $n_{h_{m,i}}$ and $n_{h_{m,f}}$ refer to the start and end samples of the harmonics, respectively; Similarly, $n_{i_{j,i}}$ and $n_{i_{j,f}}$ refer to the start and end samples of the interharmonics, respectively. 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

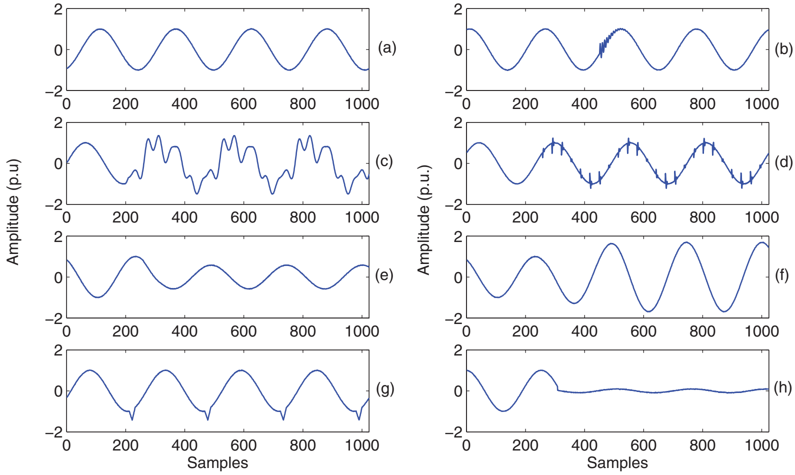


Fig. 2. Examples of voltage signals and disturbances: (a) nominal voltage signal, (b) oscillatory transient, (c) harmonics, (d) notching, (e) sag, (f) swell, (g) spikes and (h) outage.

of the $j$th interharmonic, respectively. In (5), $t_{imp}[n]$, $t_{not}[n]$ and $t_{osc}[n]$ denote impulsive transients, named spikes, notching and oscillatory transients, which can be expressed by (Ribeiro & Pereira, 2007):

$$t_{imp}[n] = \sum_{i=1}^{N_{imp}} t_{imp,i}[n][u[n - n_{t_{imp,i}}] - u[n - n_{t_{imp,f}}]], \tag{8}$$

$$t_{not}[n] = \sum_{i=1}^{N_{not}} t_{not,i}[n][u[n - n_{t_{not,i}}] - u[n - n_{t_{not,f}}]], \tag{9}$$

$$t_{osc}[n] = \sum_{i=1}^{N_{osc}} A_{osc,i}[n]exp[-\alpha_{osc,i}[n - n_{osc,i}]][u[n - n_{t_{osc,i}}] - u[n - n_{t_{osc,f}}]], \tag{10}$$

where $t_{imp,i}[n]$ and $t_{not,i}[n]$ are the $n$th samples of the $i$th spike and the $i$th notching, respectively. $n_{t_{imp,i}}$, $n_{t_{not,i}}$ and $n_{t_{osc,i}}$ denote the start of each impulsive transient and $n_{t_{imp,f}}$, $n_{t_{not,f}}$ and $n_{t_{osc,f}}$ denote the end of each.

Based in these equations, a nominal voltage waveform is shown in Figure 2(a), and some corrupted voltage waveforms are displayed in Figure 2(b)-(h), which are: (b) oscillatory transient, (c) harmonics, (d) notching, (e) sag, (f) swell, (g) spikes and (h) outage.

## 3. Higher-order statistics

Higher-Order Statistics (HOS) have been found wide applicability in many fields: sonar, radar, plasma physics, biomedicine, seismic data processing, image reconstruction, harmonic retrieval, time delay estimation, adaptive filtering, array processing and blind equalization (Mendel, 1991). An important example of HOS features is the cumulant, which is defined for various orders. The main characteristic of cumulants is to be blind to Gaussian processes.

Hence, cumulant-based signal processing tools can handle colored Gaussian measurement noise more efficiently.

The expressions of the second-, third- and fourth-order cumulants of a real and random sequence $\{x[n]\}$, such that $E\{x[n]\} = 0$, are expressed by Mendel (1991)

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

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

and

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

For a finite $N$-length vector, the stochastic approximations (Kushner & Yin, 2003) can offer the following expressions:

$$\hat{c}_{2,x}[i] = \frac{2}{N} \sum_{n=0}^{N/2-1} x[n]x\,[n+i]\,, \quad (14)$$

$$\hat{c}_{3,x}[i] = \frac{2}{N} \sum_{n=0}^{N/2-1} x[n]x^2\,[n+i] \quad (15)$$

and

$$\hat{c}_{4,x}[i] = \frac{2}{N} \sum_{n=0}^{N/2-1} x[n]x^3\,[n+i] - \frac{2}{N^2} \sum_{n=0}^{N/2-1} x[n]x\,[n+i] \sum_{n=0}^{N/2-1} x^2[n], \quad (16)$$

respectively, where $i = 0, 1, \cdots, N/2-1$, in which $i$ is called the sample lag. Note that equations (14)-(16) can not be used if $i > N/2-1$ because $n+i$ surpasses $N$, thus, alternative approximations were introduced in Ribeiro & Pereira (2007), considering $i = 0, 1, \cdots, N$. These approximations are expressed as:

$$\hat{c}_{2,x}[i] = \frac{1}{N} \sum_{n=0}^{N-1} x[n]x\,[\mathrm{mod}(n+i, N)]\,, \quad (17)$$

$$\hat{c}_{3,x}[i] = \frac{1}{N} \sum_{n=0}^{N-1} x[n]x^2\,[\mathrm{mod}(n+i, N)] \quad (18)$$

and

$$\hat{c}_{4,x}[i] = \frac{1}{N} \sum_{n=0}^{N-1} x[n]x^3\,[\mathrm{mod}(n+i, N)] - \frac{1}{N^2} \sum_{n=0}^{N-1} x[n]x\,[\mathrm{mod}(n+i, N)] \sum_{n=0}^{N-1} x^2[n], \quad (19)$$

respectively, where $\mathrm{mod}(n+i, N)$ is the integer rest of the division of $n+i$ by $N$. The approximations presented in (17-19) lead to a very appealing approach for problems where one has a finite-length vector from which higher-order-based features are extracted for applications. One has to note that the use of $\mathrm{mod}(\cdot)$ operator means that we are considering that the vector is an $N$-length periodic vector. The rationale is that by using such very simple assumption, we can evaluate the approximation of HOS with all available $N$ samples. Note that this is a heuristic approach that had emerged from the periodically nature of the voltage signals in power systems.

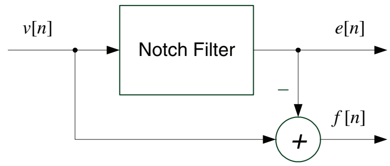


Fig. 3. Notch filter for the voltage decomposition into the fundamental and transient components.

## 4. HOS-based features for power quality monitoring

In PQ monitoring, the feature extraction based on HOS could be performed directly over voltage signals, as proposed in Ferreira, Cerqueira, Duque & Ribeiro (2009) or after pre-processing as proposed in Ribeiro et al. (2006). The pre-processing step follows the idea of signal decomposition and can be implemented by a notch filter-based methodology, which divides the acquired voltage signal $v[n]$ into two derived signals, $e[n]$ and $f[n]$, as shown in Figure 3, where the signal $e[n]$ is the remaining of $v[n]$ after filtering the fundamental component and $f[n] = v[n] - e[n]$ is an estimation of the fundamental component.
Due to the low computational cost and the reasonable selectivity in the frequency of interest, an IIR filter structure of second order has been used to design the notch filter (Hirano et al., 1974). The transfer function of the notch filter in $z$-domain is given by:

$$H_0(z) = \frac{1 + a_0 z^{-1} + z^{-2}}{1 + \rho_0 a_0 z^{-1} + \rho_0^2 z^{-2}}; \tag{20}$$

in which $a_0 = -2\cos\omega_0$, $\omega_0$ is the notch frequency, and $\rho_0$ is the *notch* factor, with $0 \ll \rho_0 < 1$. On the other hand, the usage of a non-adaptive notch filter may generate erroneous results if power frequency deviation occurs. Actually, the power frequency normally varies very slowly over a small frequency range, however for some power systems the frequency variation can be large, about 2% of its nominal value (IEEE, 2008). For resolving this problem, the usage of the *enhanced phase locked-loop* (EPLL) technique (K.-Ghartemani & Iravani, 2004), that controls the notch frequency, is an interesting solution and it is suggested for those scenarios where the power frequency variation is expected.

### 4.1 Application of HOS for feature extraction

In order to illustrate the efficiency of the HOS feature extraction for PQ monitoring, 200 events of each disturbance class (notching, spike, harmonics, outage, sag, swell and oscillatory transient) and 200 nominal voltage signals were generated following the recommendations of the IEEE standard (IEEE, 1995). A sampling frequency of 15,360 Hz and a signal to noise ratio (SNR) of 30 dB were considered. These signals were applied to the decomposition system shown in Figure 3.
Let us first analyze the signal $e[n]$. The signal was segmented into non-overlap frames with $N = 1,024$ samples (4 cycles of the fundamental component). Hence, the expressions (17) and (19) were applied to these frames and a feature vector $\mathbf{p} = [c_{2,e} \quad c_{4,e}]$ was obtained. It is important to point out that, for PQ events, the second and forth order cumulants can achieve better results with respect to the third-order cumulant, as it was been shown in Ferreira, Cerqueira, Duque & Ribeiro (2009). Therefore, for the present application, results were obtained considering only second- and forth-order cumulants. As a result of this, a total of $2 \times N$ features were extracted for each event.

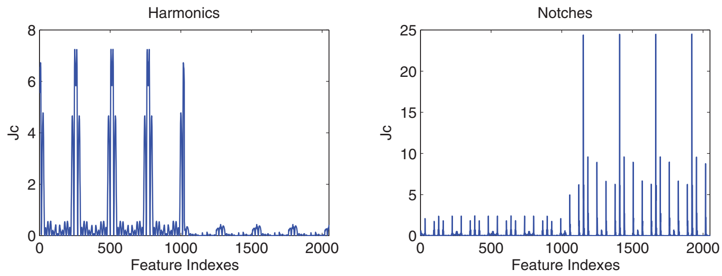


Fig. 4. Values of the FDR criterion attained for the harmonics and notching classes.

The HOS feature extraction leads to a high-dimensional feature space ($2 \times N$). Therefore, a feature selection must be performed in order to maximize the separation border between classes and also to reduce the dimension of the feature space and consequently the computational burden and processing time. In this context, some feature selection techniques (Duda et al., 2000) can be used. Recent works, such as de Aguiar et al. (2009); Ferreira, Cerqueira, Duque & Ribeiro (2009); Ferreira, de Seixas & Cerqueira (2009) have used the Fisher's discriminant ratio (FDR) (Duda et al., 2000) for feature selection, which is given by

$$\mathbf{J}_c = \mathbf{\Lambda}_{\mu_0,\mu_1}\mathbf{\Lambda}^{-1}_{\sigma_0,\sigma_1}, \tag{21}$$

in which

$$\mathbf{\Lambda}_{\mu_o,\mu_1} = diag\{(\mu_{0,1}-\mu_{1,1})^2,\ (\mu_{0,2}-\mu_{1,2})^2, \dots, (\mu_{0,N}-\mu_{1,N})^2\} \tag{22}$$

and

$$\mathbf{\Lambda}_{\sigma_o,\sigma_1} = diag\{(\sigma^2_{0,1}+\sigma^2_{1,1}),\ (\sigma^2_{0,2}+\sigma^2_{1,2}), \dots, (\sigma^2_{0,N}+\sigma^2_{1,N})\}. \tag{23}$$

Assuming that $\mathbf{x}_{FDR}$ is constituted by the element in the main diagonal of the matrix $\mathbf{J}_c$, such that $x_{FDR}(1) > x_{FDR}(2) > \cdots > x_{FDR}(N)$, then, a set of $k$ features associated with the $k$ highest values in the vector $\mathbf{x}_{FDR}$ can be selected.

Figure 4 illustrates the FDR ($\mathbf{J}_c$) for the harmonics against all other classes and notching against all other classes, obtained using the feature vector $\mathbf{p}$. The first indexes $(1...1,024)$ comprise the second order cumulants ($c_{2,e}$), and the remaining comprise the fourth order cumulants ($c_{4,e}$). These examples point out that for some classes, the second order cumulant is more discriminative than fourth order, as it could be seen for harmonics and the other way round for other classes, as it can be seen for notching disturbances. Therefore, the combination of both second and fourth order cumulants is powerful, since they carry distinct information, as discussed in Mendel (1991).

Figure 5 shows the discrimination capability of the second and fourth order cumulants. Analyzing the events in the feature space, it is possible to notice that notching, nominal voltage waveforms, sags, swells and outages are more homogeneous classes, while harmonics, spikes and oscillatory transients classes are scattered in the feature space. It is also important to notice that there are only interceptions between the nominal voltage, sag and swell signals. Therefore, most classes may be separated using just these two features.

Additionally, the usage of the information related to the fundamental component ($f[n]$) may lead to a better separation between the nominal voltage, sag and swell signals. Figure 6 shows the feature space obtained with cumulants that were extracted from the fundamental

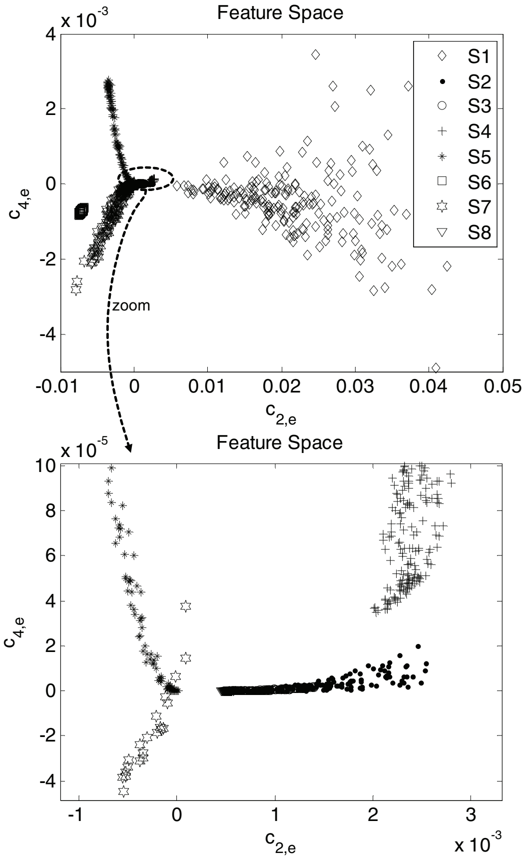


Fig. 5. Feature space for: (S1) harmonics, (S2) sag, (S3) swell, (S4) outage, (S5) spike, (S6) notching, (S7) oscillatory transient and (S8) nominal voltage waveform.

component. In this new feature space it is easy to recognize the nominal voltage, sag and swell classes.

## 5. Disturbance detection and classification based on HOS

In this section, the HOS based features are used for automatic detection and classification of PQ disturbances. Once the cumulant based features are extracted from the incoming signal, the next step consists in applying the detection and classification techniques. At this point, it is important to consider the computational complexity of the chosen techniques. In general, the techniques with high performance may lead to large computational cost. Then, the challenge is to develop a low-complexity technique that achieves high performance.

### 5.1 PQ disturbances detection using HOS

The aim of the detection techniques is to provide a real-time and source reliable detection of a variety of disturbances, so that event classification and underlying identification can be both

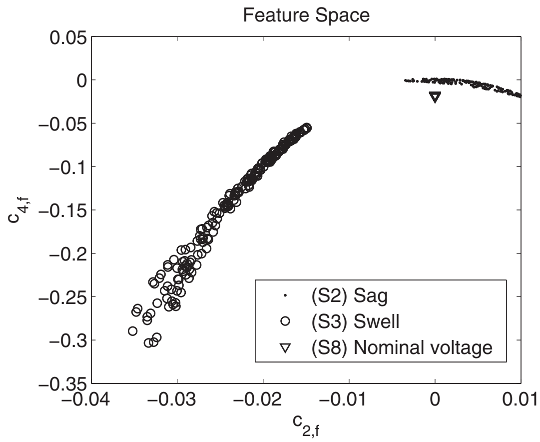


Fig. 6. Feature space for: (S2) sag, (S3) swell and (S8) nominal voltage waveform.

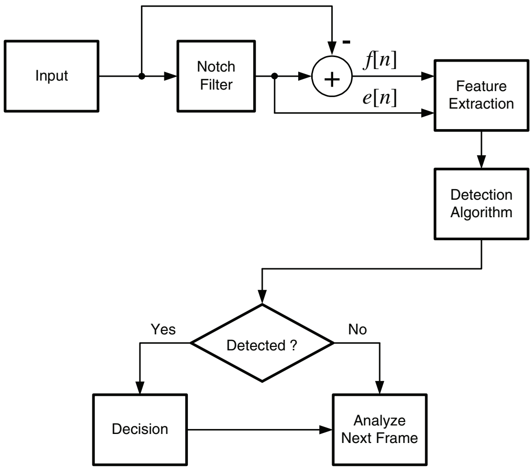


Fig. 7. Detection system.

achieved. Several methods have been proposed in the literature and the most used techniques are based on wavelet transforms (WT) (Chen et al., 2009; Lin et al., 2008; Wang & Wang, 2007; Yang & Liao, 2001). However, the attained results with WT may be seriously affected by the system noise (Yang & Liao, 2001). Other methods that may be mentioned include S-transform (Bhende et al., 2008; Mishra et al., 2008), Hilbert transform (Chun-Ling et al., 2009), fractals (Li et al., 2005) and support vector machines (Moraveja et al., 2010). Each of these techniques have advantages and disadvantages. Disturbance detection based on HOS have the following characteristics: i) it is more insensitive to the presence of background noise; and ii) it is capable of detecting the occurrence of disturbances in frames corresponding to 1/16 of the fundamental component. As a result, the HOS-based techniques can be used in noisy applications and situations where the detection of disturbances in frames whose lengths correspond to submultiples or multiples of one fundamental cycle is needed.

Figure 7 portrays the block diagram of a HOS-based detection technique proposed in Ribeiro et al. (2007). In this diagram, the Input block contains discrete samples of the power line signal and the block NF0 implements a infinite impulse response (IIR) digital notch filter given by Equation (20). Subsequently, two discrete signals are generated which are, the fundamental component $f[n]$ and the error component $e[n]$. Then, 2nd and 4th order's cumulants of $N$-length vectors constituted by samples of $f[n]$ and $e[n]$ are extracted by the Feature Extraction block. During the design stage, the Fisher's criterion is applied in order to select the best features, as explained in Section 4. Then, in the operational stage, only the previously chosen features are computed. Finally, the Detection Algorithm block performs the decision by using a Bayesian detector (Trees, 2001) based on maximum likelihood criterion (Theodoridis & Koutroumbas, 2006).
Considering the vectors $\mathbf{f} = [f[n] \cdots f[n-N-1]]^T$ and $\mathbf{e} = [e[n] \cdots e[n-N-1]]^T$ built from samples of the signals $f[n]$ and $e[n]$, respectively, the detection problem can be formulated as a hypothesis test problem (Ribeiro et al., 2007).

$$\begin{aligned} \mathcal{H}_1 &: \mathbf{e} = \mathbf{r}_e \\ \mathcal{H}_2 &: \mathbf{f} = \mathbf{f}_{ss} + \mathbf{r}_f \\ \mathcal{H}_3 &: \mathbf{e} = \mathbf{i} + \mathbf{t} + \mathbf{h} + \mathbf{r}_e \\ \mathcal{H}_4 &: \mathbf{f} = \mathbf{f}_{ss} + \Delta\mathbf{f}_{ss} + \mathbf{r}_f, \end{aligned} \tag{24}$$

where $\mathbf{i} = [i[n] \cdots i[n-N-1]]^T$, $\mathbf{t} = [t[n] \cdots t[n-N-1]]^T$, $\mathbf{h} = [h[n] \cdots h[n-N-1]]^T$, $\mathbf{r}_e + \mathbf{r}_f = \mathbf{r} = [r[n] \cdots r[n-N-1]]^T$. The vector $\Delta\mathbf{f}_{ss}$ represents a sudden variation in the fundamental component and the vector $\mathbf{f}_{ss}$ denotes the steady-state component of the fundamental component. The hypotheses formulation introduced in (24) emphasizes the need to analyze abnormal events through the so-called primitive components of voltage signals that are represented by the vectors $\mathbf{f}$ and $\mathbf{e}$. While the hypotheses $\mathcal{H}_1$ and $\mathcal{H}_2$ are related to standard operation, both hypotheses $\mathcal{H}_3$ and $\mathcal{H}_4$ are associated with abnormal conditions. Equation (24) means that we are looking for some kind of abnormal behavior in one or two primitive components of the input signal, so that a decision about disturbance occurrences can be accomplished. This concept is very attractive, because the vectors $\mathbf{f}_{ss} + \Delta\mathbf{f}_{ss} + \mathbf{r}_f$ and $\mathbf{i} + \mathbf{t} + \mathbf{h} + \mathbf{r}_e$ can reveal insightful and different information from the voltage signals.
Although four hypotheses are given in (24), for the detection problem we can consider only two hypotheses: the hypothesis $\mathcal{H}_a = \mathcal{H}_1 \cup \mathcal{H}_2$ which comprises standard operational condition of the monitored voltage signal and hypothesis $\mathcal{H}_b = \mathcal{H}_3 \cup \mathcal{H}_4$, which comprises abnormal conditions (disturbances). Based on the Bayes decision theory (Theodoridis & Koutroumbas, 2006), the detection through the vector $\mathbf{p}$, which was selected by the FDR, can be performed as follows:

$$\frac{p(\mathbf{p}|\mathcal{H}_b)}{p(\mathbf{p}|\mathcal{H}_a)} \underset{\mathcal{H}_b}{\overset{\mathcal{H}_a}{\gtrless}} \frac{P(\mathcal{H}_a)}{P(\mathcal{H}_b)}, \tag{25}$$

where $P(\mathcal{H}_i)$, $i = a, b$, represents the *a priori* probability and $p(\mathbf{p}|\mathcal{H}_i)$ represents the conditional probability density function of the class $\mathcal{H}_i$. The conditional probability density function used here is expressed by

$$p(\mathbf{p}|\mathcal{H}_i) = \frac{1}{(2\pi)^{L/2} |\sum_i|^{1/2}} e^{-\frac{1}{2}(\mathbf{p}-\mu_i)^T \sum_i^{-1} (\mathbf{p}-\mu_i)}, \tag{26}$$

| $N$ | Detection Rates (%) |
|---|---|
| 256 | 100 |
| 128 | 100 |
| 64 | 99.8 |
| 32 | 99.8 |
| 16 | 98.6 |

Table 1. Detection rates for disturbance detection

where $\mu_i = E\{\mathbf{p}\}$ is the average vector of the class $\mathcal{H}_i$, $\sum_i$ is the covariance matrix of the same class defined as

$$\sum\nolimits_i = E\{(\mathbf{p} - \mu_i)(\mathbf{p} - \mu_i)^T\}, \tag{27}$$

and $|\sum_i|$ denotes the determinant of $\sum_i$. Note that $\mu_i$ and $\sum_i$ are obtained in the design stage. Supposing that $P(\mathcal{H}_a)$=$P(\mathcal{H}_b)$=1/2 and assuming the probability density functions referred in (26) the detector described in (25) assumes the following form:

$$\frac{|\sum_a|^{\frac{1}{2}}\ e^{-\frac{1}{2}(\mathbf{x}-\mu_b)^T \sum_b^{-1}(\mathbf{p}-\mu_b)}}{|\sum_b|^{\frac{1}{2}}\ e^{-\frac{1}{2}(\mathbf{p}-\mu_a)^T \sum_a^{-1}(\mathbf{p}-\mu_a)}} \underset{\mathcal{H}_b}{\overset{\mathcal{H}_a}{\gtrless}} 1, \tag{28}$$

Thus, the left side of (28) is applied to the feature vector, and if the evaluated value is higher or equal to 1, a disturbance in the voltage signal is detected, otherwise, the voltage signal is considered to be without any disturbance.

#### 5.1.1 Results

To verify the performance of the detection technique, simulations were carried out with several waveforms of voltage signals with signal-to-noise rate (SNR) equals to 30 dB and sampling rate $f_s = 256 \times 60$ Hz. The generated disturbances, with 600 waveforms each, were sag, swell, outages, oscillatory transient, notching, spikes and harmonics. In order to show how detection efficiency deteriorates with a reduced number of samples, the number of samples used to detect the disturbances were $N$= 256, 128, 64, 32 and 16 samples. The notch factor of the notch filter was 0.997. The achieved results in terms of detection rates are presented in Table 1. It is important to note that detection rates are higher than 98 %, even when only 16 samples are considered.

### 5.2 PQ disturbance classification using HOS

An important step in designing pattern recognition systems is the feature extraction, which aims to find the best features **p** envisaging classes separation on the feature space. The application of cumulant-based features for disturbance classification, proved to be efficient, as from the results obtained by Ferreira, Cerqueira, Duque & Ribeiro (2009). However, this work did not consider power line signals corrupted by various disturbances occurring simultaneously, i.e., multiple disturbances. In this context, Ribeiro & Pereira (2007) proposed the principle of divide and conquer, which was applied to decompose an electric signal into a set of primitive components for classification of single and multiple disturbances in electric network. In the present chapter, the main goal of the pre-processing is to decouple the multiple disturbances into single disturbances before classifying. This procedure is motivated

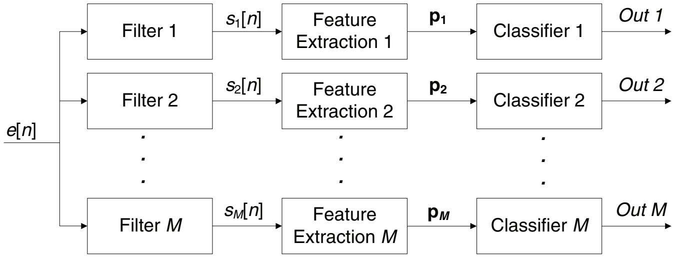


Fig. 8. Filter bank for disturbance decoupling.

by the assumption that the voltage signal is composed by the additive contribution of several types of disturbances, as formulated in (1).

Nevertheless, a digital filter bank may be used to decouple multiple disturbances (Ferreira et al., 2010). According to IEEE (1995), each disturbance class is well defined in terms of specific variables, such as magnitude, frequency range, and others. Hence, a well defined set of simulated disturbances may provide consistent spectral information about each class and, then, a simple and efficient filter bank can be designed. Figure 8 illustrates the filtering approach. The signal $e[n]$ is firstly filtered and the output of each filter is individually analyzed. Each classifier can be designed to be assign to a specific class or a reduced group of classes. Finally, the outputs *Out 1*, *Out 2*, ..., *Out M* feed a final logic which defines the type of disturbance (multiple or single) presented in $e[n]$. The final logic may also incorporate information based on $f[n]$, which is very important to separate standard events from sags and swells, as shown in Section 4.

### 5.2.1 Classifier design

A block diagram of the automatic classification system proposed in Ferreira et al. (2010) can be seen in Figure 9. The disturbances related to the fundamental component (sags and swells) are handled directly using second and fourth order cumulants. The filter bank was designed using the spectrum content of the disturbances related to the error signal $e[n]$ (harmonics, transients and notching). In such a way, the majority of the energy from the harmonic is presented at the output of Filter 1 ($s_1[n]$), which is a low-pass filter with cut-off frequency $f_C$=500 Hz. The high-pass filter (Filter 3) with $f_c$=3 kHz selects the disturbances with high frequencies in its output ($s_3[n]$), which in this case corresponds mainly to notching class of disturbance. Filter 2 is a band-pass filter with $f_{Ci}$=500 Hz and $f_{Cs}$=3 kHz, which basically reduces the energy from harmonics and notching from the remaining disturbances (oscillatory transients and spikes) at its output.

Considering the filtering approach, the classification problem can be formulated as the following:

(i) From signal $f[n]$, the hypothesis test for disturbance classification for the fundamental component becomes:

$$\begin{aligned}
\mathcal{H}_{f,1} &: \mathbf{f} = \mathbf{f}_{ss} + \mathbf{r}_f \\
\mathcal{H}_{f,2} &: \mathbf{f} = \mathbf{f}_{under} + \mathbf{r}_f \\
\mathcal{H}_{f,3} &: \mathbf{e} = \mathbf{f}_{over} + \mathbf{r}_f \\
\mathcal{H}_{f,4} &: \mathbf{f} = \mathbf{f}_{inter} + \mathbf{r}_f,
\end{aligned} \tag{29}$$

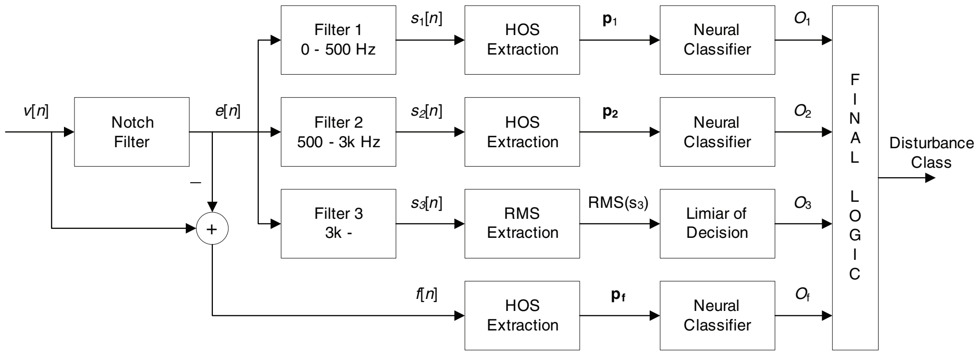


Fig. 9. Classification system.

where the vectors $\mathbf{f}_{under}$, $\mathbf{f}_{over}$, and $\mathbf{f}_{inter}$ denote an undervoltage or sag, a disturbance called overvoltage or swell, and a disturbance named sustained interruption or outage, respectively.

(ii) From signal $s_1[n]$, disturbance classification for the error component is formulated as:

$$\begin{aligned} \mathcal{H}_{s_1,1} : \mathbf{s}_1 &= \mathbf{r}_{s_1} \\ \mathcal{H}_{s_1,2} : \mathbf{s}_1 &= \mathbf{h} + \mathbf{r}_{s_1}, \end{aligned} \tag{30}$$

where $\mathbf{s}_1 = [s_1[n] \cdots s_1[n-N-1]]^T$ and $\mathbf{r}_{s_1}$ is the filtered version of the noise vector $\mathbf{r}$ by Filter 1.

(iii) From signal $s_2[n]$, the classification of disturbances in the error component is formulated as:

$$\begin{aligned} \mathcal{H}_{s_2,1} : \mathbf{s}_2 &= \mathbf{r}_{s_2} \\ \mathcal{H}_{s_2,2} : \mathbf{s}_2 &= \mathbf{t}_{osc} + \mathbf{r}_{s_2} \\ \mathcal{H}_{s_2,3} : \mathbf{s}_2 &= \mathbf{t}_{imp} + \mathbf{r}_{s_2}, \end{aligned} \tag{31}$$

where $\mathbf{t}_{osc} = [t_{osc}[n] \cdots t_{osc}[n-N-1]]^T$, $\mathbf{t}_{imp} = [t_{imp}[n] \cdots t_{imp}[n-N-1]]^T$ and $\mathbf{r}_{s_2}$ is the filtered version of the noise vector $\mathbf{r}$ by Filter 2.

(iv) From signal $s_3[n]$, disturbance classification for the error component is formulated as:

$$\begin{aligned} \mathcal{H}_{s_3,1} : \mathbf{s}_3 &= \mathbf{r}_{s_3} \\ \mathcal{H}_{s_3,2} : \mathbf{s}_3 &= \mathbf{t}_{not} + \mathbf{r}_{s_3}, \end{aligned} \tag{32}$$

where $\mathbf{t}_{not} = [t_{osc}[n] \cdots t_{not}[n-N-1]]^T$ and $\mathbf{r}_{s_3}$ is the filtered version of the noise vector $\mathbf{r}$ by Filter 3.

The three filters were designed as IIR (Infinite Impulse Response) (Mitra, 2005) of fourth order (see Equation (33)). The elliptic approximation was used for designing the filters. Elliptic filters have an equiripple pass-band and an equiripple stop-band. Because the ripples are distributed uniformly across both bands, these filters are optimum in the sense of having the smallest *transition* width for a given filter order, cut-off frequency and pass-band and stop-band ripples (Mitra, 2005).

$$H(z) = \frac{b_0 + b_1 z^{-1} + \cdots + b_4 z^{-4}}{a_0 + a_1 z^{-1} + \cdots + a_4 z^{-4}} \tag{33}$$

The block diagram (Figure 9) shows that the HOS features are extracted for $s_1[n]$, $s_2[n]$ and $f[n]$. As signal $s_3[n]$ is mainly composed by notching, a simple feature extraction was used (the root mean squared value (RMS)). As for the detection system presented in Section 5.1, the 2nd and 4th order's HOS features of $N$-length vectors constituted by samples of $s_1[n]$, $s_2[n]$ and $f[n]$ were extracted and the Fisher's criterion was applied in order to select the best features.

The Bayesian classifier minimizes the error probability, however, not all problems are well suited to such approaches as the involved probability density functions are complicated and their estimation is not an easy task. In such cases, it may be preferable to compute decision surfaces directly by means of alternative costs, as is the case of the neural networks, support vector machines, etc. Therefore, for the classification of power quality disturbances, several works use neural networks, support vector machines, fuzzy classifiers, decision threes, among others.

In Ferreira et al. (2010), for each vector of extracted features given by $\mathbf{p}_1$, $\mathbf{p}_2$ and $\mathbf{p}_3$, an expert pattern recognition system was be used. Due to its good ability to distinguish disturbances, a reduced number of cumulants is enough, as discussed in Section 4. Consequently, simple neural classifiers may be used. This is an important advantage in classification systems, mainly for real-time applications. The three pattern recognition systems used were from multilayer feedforward artificial neural networks (Haykin, 2009). The neural networks comprise a single hidden layer. The RPROP algorithm (Riedmiller & Braun, 1993) was used to train the neural classifiers. The hyperbolic tangent was used as activation function. For $RMS(s_3)$, a simple threshold was used.

The Final Logic block combines the classifier outputs $O_1$, $O_2$, $O_3$ and $O_f$, using a logical operation based on the logical gate AND. Thus, a large group of multiple disturbance classes can be easily incorporated by the Final Logic block.

### 5.2.2 Results

The following disturbance classes were considered in this application: outages; harmonics; sags; swells; oscillatory transients; notching; spikes; sag with harmonics; swell with harmonics; sag with oscillatory transient; swell with oscillatory transient; sag with notching; swell with notching; notching with harmonics; oscillatory transient with harmonics; sag with oscillatory transient and harmonics; sag with notching and harmonics; swell with notching and harmonics; and swell with oscillatory transient and harmonics. Figure 2 (b)-(h) illustrates examples of single disturbances. Examples of multiple disturbances are illustrated in Figure 10.

Five hundred events from each class were simulated. Three hundred of each class were used to design the classifier and the remaining data were used for testing. The classification design comprises the design of filters, the feature selection and the neural training. The achieved results can be seen in Table 2.

The main advantage of this system is its capability of classifying multiple disturbances with reasonable efficiency. Eight classes comprising two simultaneous disturbances and four classes formed by three simultaneous disturbances were correctly classified with efficiencies above 97.2 %, as shown in Table 2. Additionally, others classes of multiple disturbances can be addressed by combining the classifier outputs $O_1$, $O_2$, $O_3$ and $O_f$ through the Final Logic.

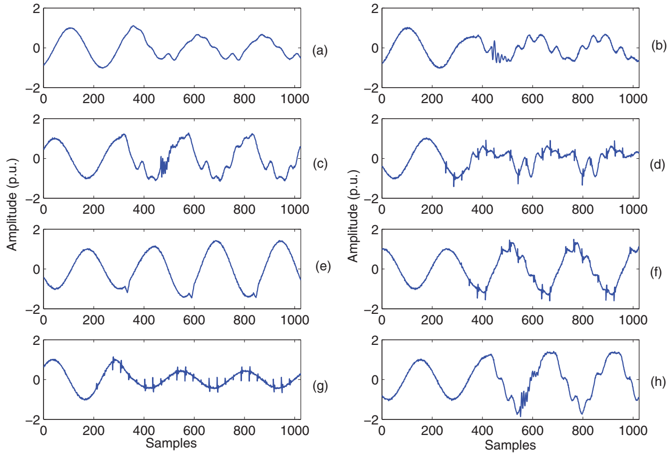


Fig. 10. Examples of multiple disturbances: (a) sag with harmonics, (b) sag with oscillatory transient and harmonics, (c) oscillatory transient with harmonics, (d) sag with notching and harmonics, (e) swell with spikes, (f) swell with notching and harmonics, (g) sag with notching, and (h) swell with oscillatory transient and harmonics.

| Disturbance Classes | Efficiency in % |
|---|---|
| Outage | 100 |
| Harmonics | 99.0 |
| Sag | 100 |
| Swell | 100 |
| Oscillatory Transient | 99.0 |
| Notching | 100 |
| Spike | 100 |
| Sag + harmonics | 99.0 |
| Swell + harmonics | 97.2 |
| Sag + oscillatory transient | 100 |
| Swell + oscillatory transient | 99.4 |
| Sag + notching | 100 |
| Swell + notching | 99.0 |
| Notching + harmonics | 99.4 |
| Oscillatory transient + harmonics | 98.2 |
| Sag + oscillatory transient + harmonics | 98.2 |
| Sag + notching + harmonics | 98.4 |
| Swell + notching + harmonics | 98.8 |
| Swell + oscillatory transient + harmonics | 97.8 |

Table 2. Classification results based on a filter bank.

## 6. Conclusions

The performance of the PQ monitoring system is directly related to the pre-processing and feature extraction techniques used. Therefore, the identification of efficient pre-processing and feature extraction techniques is very important.
The usage of HOS as a feature extraction technique for PQ monitoring systems is very promising and several recent works presented good results with respect to both detection and classification tasks.
The main advantages of the HOS as a feature extraction technique is its immunity to Gaussian noise and also the capability to reveal non-linear characteristics from the data, which is important for pattern recognition applications.
Some results shown that HOS is able to detect disturbances even using short acquisition time windows, which represents an important characteristic for several power systems applications such as protection, signal segmentation and disturbance localization. Being specific, the results shown that the detection of disturbances can be accomplished in less than a quarter of cycle, which is excellent for protection application, where speed and accuracy need to be combined to guarantee selectivity and reliability during the occurrence, for example, of a fault in a system.
Regarding the usage of HOS in PQ classification, the results shown that combining techniques allows efficient classification of single and simultaneous disturbances, and more, the usage of the second and fourth orders HOS features, for a specific lag chosen from the FDR criterion, has been enough to deal with the majority of the disturbances considered.

## 7. Future trends

Several problems in PQ are still open. Among them, load identification and source localization, both related to each other. Given that the PQ Analyzer has detected and classified a disturbance, what kind of event and load have caused that problem?
For example, if a sag is detected and classified, the next step is answering if that sag was generated by a fault in the system or by a start of a big motor. If a transient is detected, what kind of event has caused it, a fault or a switching capacitor bank? Can HOS be used to overcome this problem? These questions are under investigation at the moment.
Other promising application of HOS is in protection issues. HOS can be used in fault detection, classification and localization as shown by recent works, but there are a few works in this area and several questions to be answered. The challenge is to guarantee simultaneously speed, reliability and selectivity.
Another area where HOS can bring good results is in diagnose of electrical equipments, such as transformers, motors and generators. Can cumulants, of voltage and current signals, carry useful information about the status of the equipment? All these questions surely make PQ research attractive and full of challenges.

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