ICA-based Method for Power Quality Disturbance Analysis

Danton D. Ferreira, José M. de Seixas and Augusto S. Cerqueira

Abstract--This paper presents a new methodology based on Independent Component Analysis (ICA) for power quality disturbance analysis. The proposed methodology aims at analyzing power quality disturbances that appear as mixtures in the voltage signal. Such disturbances are commonly referred to as multiple disturbances. Results are obtained from both simulated and experimental data showing that disturbance classification higher than 97 % can be achieved. The results are attractive for practical applications in power quality systems.

Index Terms -- ICA, Power Quality, Multiple Disturbances.

I. Introduction

ELECTRIC power quality has become an active research area in the last few years due to the growing concern of delivering clean power to consumers in the presence of distorted waveforms [1]. Waveform distortions are normally caused by disturbances such as voltage sag/swell with and without harmonics, momentary interruption, harmonic distortion, flicker, notch, spike and transients, causing problems such as malfunctions, instabilities, short lifetime, and failure of electrical equipments and so on [2].

According to [3], electric distribution network faults may cause voltage sag or momentary interruption whereas switching off large loads or energizing large capacitor banks may lead to voltage swell. On the other hand, the use of solid-state switching devices and nonlinear power electronically switched loads such as rectifiers or inverters may cause harmonic distortion and notching in the voltage and current signals. Flickers may be caused by the usage of arc furnaces and ferroresonance. Transformer energizing or capacitor switching may cause transients, whereas lightning strikes may lead to spikes.

In this context, several signal processing and computational intelligence techniques have been proposed for power quality (PQ) monitoring [2]. These techniques try to achieve high performance with low computational complexity, which is required for online PQ monitoring.

The PQ monitoring comprises, basically, two processing stages: disturbance detection and classification. Typically, this is developed using the voltage waveform. Recently, a bunch of methods have been proposed for the automatic recognition of the PQ disturbances [3,4,5]. These methods are capable of recognizing the PQ disturbances with promising accuracy rate. However, these methods aim at recognizing single PQ disturbance in a measured voltage waveform. Thus, the performance of these methods might be limited because, in real power systems, the disturbances could appear simultaneously. These events are commonly referred to as multiple disturbances. Some efforts have been done about this problem, where the works [6] and [7] stand out, but further studies are still required.

This paper proposes a new methodology based on Independent Component Analysis (ICA) [8] for analyzing PQ events with multiple disturbances, following the idea first proposed in [9]. Here, ICA is applied in order to decouple the multiple disturbances envisaging the improvement of the classification efficiency.

This paper is organized as follows. Section II formulates the multiple disturbance PQ problems. Section III presents the fundamentals of the ICA theory. Section IV describes the proposed method and Section V presents the achieved results. Conclusions are derived in Section VI.

II. Problem Formulation

According to [6], monitoring the discrete version of powerline signals can be achieved through non-overlapped frames of N samples each. The discrete sequence in a frame is expressed as an additive contribution of several types of phenomena:

$$v(n) = v(t)|_{t=nT_s} := f(n) + h(n) + i(n) + t(n) + r(n), \qquad (1)$$

where $n=0,\dots,N-1$, $T_s=1/f_s$ is the sampling period, the sequences $\{f(n)\}$, $\{h(n)\}$, $\{i(n)\}$, $\{t(n)\}$ and $\{r(n)\}$ denote the fundamental component, harmonics, interharmonics, transient and background noise, respectively. Each of these signals is defined in details in [6].

So far, most classification techniques are developed for single disturbance analysis. Nevertheless, one can note that the incidence of multiple disturbances, at the same time interval, in electric signals, is an ordinary situation due to the presence of several sources of disturbances in the power systems.

Figure 1 displays two typical cases. These voltage measurements were obtained from the IEEE working group P1159.3 website [10]. In Figure 1(a), one can note the incidence of a short-duration voltage variation named sag,

D. D. Ferreira is with the Federal University of Lavras, UFLA, Lavras, MG, Brazil, emails: danton@ufla.br.

Seixas is with the Federal University of Rio de Janeiro, COPPE/Poli, Rio de Janeiro, RJ, Brazil, e-mail: seixas@lps.ufrj.br.

A. S. Cerqueira is with Department of Electrical Circuits, Federal University of Juiz de Fora, Juiz de Fora, MG, Brazil, e-mail: augusto.santiago@ufjf.edu.br

harmonics and short-transient intervals. In Figure 1(b), disturbances comprise harmonics, transients that can be *a priori* assumed to be a decaying oscillation, and possibly, other type of disturbances, which are quite difficult to be categorized *a priori*.

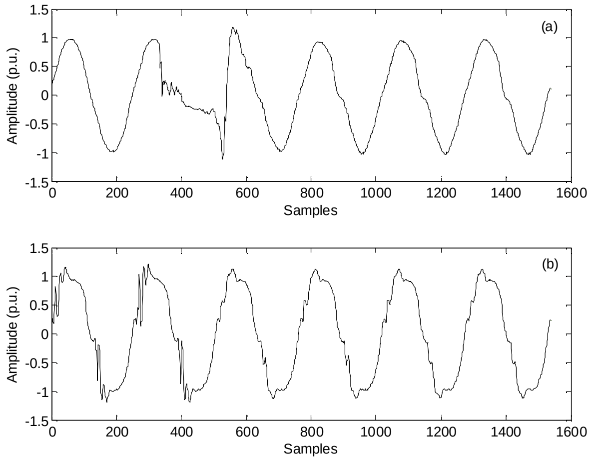


Fig. 1. Examples of multiple disturbances in monitored voltage signals.

Observing Equation (1), the processing target is to decouple the multiple disturbances. This is the case of ICA, which, in this context, aims at separating blindly the original disturbance sources that build the acquired voltage signal.

III. Independent Component Analysis

ICA is a statistical transformation that aims at decomposing an observed multi-dimensional vector into mutually independent source components [8]. The ICA transformation searches for source signals that are as much independent as possible. The basic ICA definition can be expressed as

$$\mathbf{x}(n) = \mathbf{A}\mathbf{s}(n), \tag{2}$$

where $\mathbf{x}(n) = [x_1(n), x_2(n), \ldots, x_M(n)]^T$ is the observed vector at sample n, $\mathbf{s}(n) = [s_1(n), s_2(n), \ldots, s_N(n)]^T$ is the statistically mutually independent component vector at sample n and $\mathbf{A}$ is an M x N scalar matrix, which is called the mixing matrix.

The ICA algorithms estimate the original source signals blindly, i.e, using only the observed signals:

$$\mathbf{y}(n) = \mathbf{W}\mathbf{x}(n). \tag{3}$$

In this equation, $\mathbf{y}(n) = [y_1(n), y_2(n), \ldots, y_N(n)]^T$ represents the estimation of the independent components $s_i(n)$ and $\mathbf{W}$ is the demixing matrix. The basic mode assumes $M = N$.

In a PQ monitoring application, only one monitoring device is available. In this case, $M < N$ and the problem is called overcomplete [11], due to scarcity of dimension in the mixture space. There is a reasonable number of proposals in order to solve this problem [11,12,13]. However, the proposed solutions in the current literature demand a high computational cost and are often developed for practical specific applications. Thus, in this paper, a new method for analyzing PQ multiple disturbances is proposed where only one device is monitored.

As from the ICA model, we assume that the original disturbances are, at each time instant t, statistically independent. Conceptually, random variables, $y_1, y_2, \ldots, y_N$ are said to be independent if the information on the value of y_i does not give any information on the value of y_j, for $i \neq j$. Adapted to our application, this means that the information of one disturbance does not give any information about the other disturbances. Also, we assume that the original disturbances have nongaussian distributions [8].

The FastICA algorithm [14] was used in this work. It is based on a fixed-point iteration scheme and, basically, consists of two steps: preprocessing and the FastICA algorithm itself. The preprocessing step consists of centering and whitening the data [8]. The centering of the data is performed by subtracting the mean of the data from the incoming signal in a processing frame. Data whitening is used to remove the correlation between the observed data [8].

IV. Proposed Method

The proposed method to decouple multiple disturbances can be basically split into blocks, as it is displayed in Figure 2.

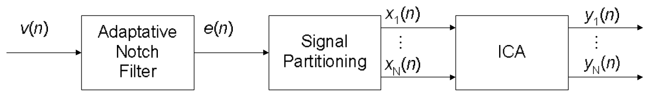


Fig. 2. Block diagram of the proposed method.

The first stage comprises an adaptive notch filter employed for removing the fundamental component of the power system voltage signal $\{v(n)\}$. Thus, the remaining signal after the first stage contains only PQ disturbance information, except for the sags, swells and interruptions that are PQ disturbances related to the fundamental component. The adaptive notch filter structure used is PLL (phased-locked loop), as proposed in [15]. The PLL provides three advantages when compared to a classical notch filter [14] that are: (i) no phase difference between the estimated fundamental component and the input signal. Thus, the error signal is synchronized with the input signal; (ii) real time estimation of fundamental component amplitude and phase; and (iii) it is a robust structure with respect to internal parameter variations, external noise and small variations of system fundamental frequency.

The second stage concerns partitioning the resulting signal $e(n)$ into N signals $\{x_1(n)\}$, $\{x_2(n)\}$, $\ldots$, $\{x_N(n)\}$ through a sliding window. The first signal $\{x_1(n)\}$ is from an acquisition window of $e(n)$ (1,024 samples). The next signal $\{x_2(n)\}$ is from shifting the window by one sample. The partitioning follows by using one sample sliding windows. In the last stage, the set of N acquired signals is applied to the FastICA algorithm, which aims at providing the output of the isolated disturbances $\{y_1(n)\}$, $\{y_2(n)\}$, $\ldots$, $\{y_N(n)\}$.

V. Results

The goal of this section is to present results obtained using real and simulated data, which point out the capability of the proposed ICA-based method to decouple multiple electrical disturbances.

As an illustrative example, Figure 3 shows a window with 1,024 samples (4 fundamental cycles) of a simulated signal that contains harmonics and notches disturbances. This signal was simulated by software according to the IEEE standards [17], with a sampling frequency of 15,360 Hz.

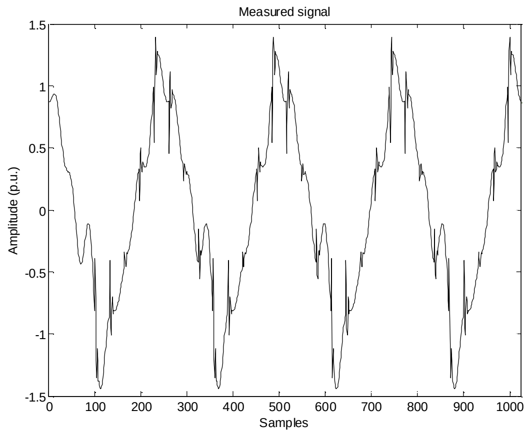


Fig. 3. Simulated signal containing two disturbances (notch and harmonics).

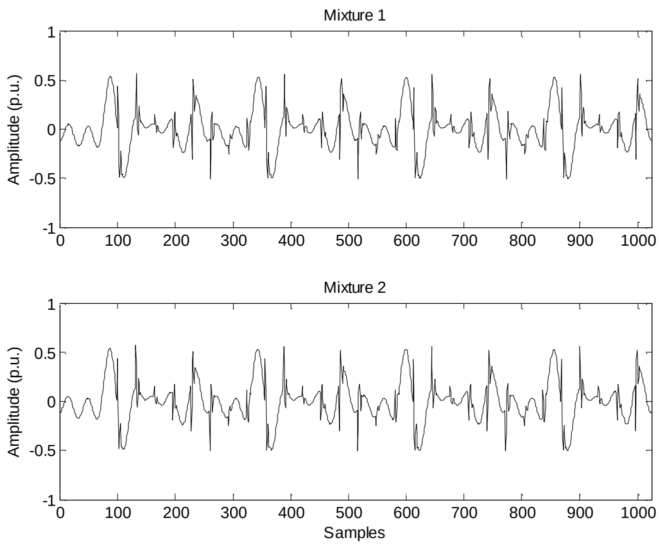


Fig. 4. Simulated mixtures that feed the ICA algorithm.

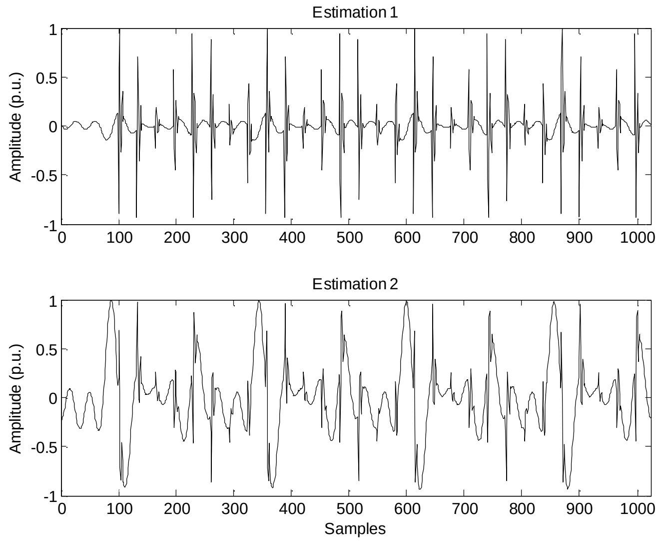
The fundamental component was removed by the adaptive notch filter according to the procedure described in Section IV. After signal partitioning, two mixtures (1,024 samples) were generated, as it is shown in Figure 4.

Figure 5 shows the normalized output estimations of the FastICA algorithm and Figure 6 shows the corresponding normalized original sources. Qualitatively, the similarity between the estimation and the original notch disturbance can be noticed from these figures, although small residues from the mixture are observed.

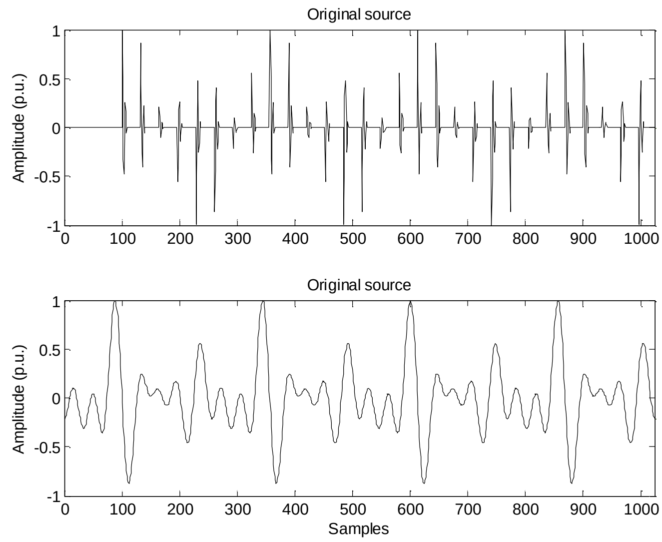
Considering now signals corrupted from capacitor switching and harmonics, the same procedure was applied and results are displayed in Figure 6, which shows a similar result with respect to harmonics and notch disturbances.

Aiming at improving the ICA estimations, the underdetermined case was explored. Now, three mixtures $\{x_1(n)\}$, $\{x_2(n)\}$ e $\{x_3(n)\}$ were presented to the FastICA algorithm. The same procedure was applied for three mixtures of each multiple disturbance and the estimated sources are displayed in Figures 7 and 8. A significant improvement can be verified in the estimated sources, as the mixture residues were considerably reduced.

To evaluate the impact of the estimation source quality of the proposed method on the classification task, a multi-layer perceptron neural network [18] was fed from original sources for the training phase and tested using the estimated source signals obtained by the ICA-based method. The neural network target was to classify notches, capacitor switching and harmonics disturbances. The layer's weights and biases were initialized according to the Nguyen-Widrow initialization algorithm [19]. The activation function was the hyperbolic tangent sigmoid. The RPROP algorithm [20] was used to train the network.



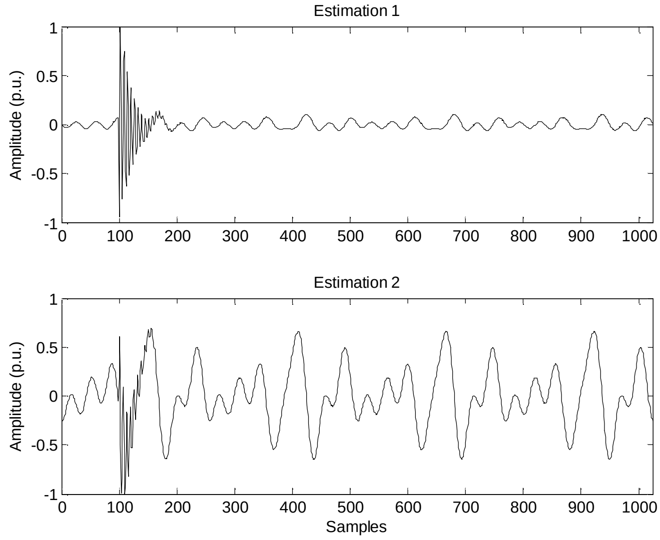
(a)



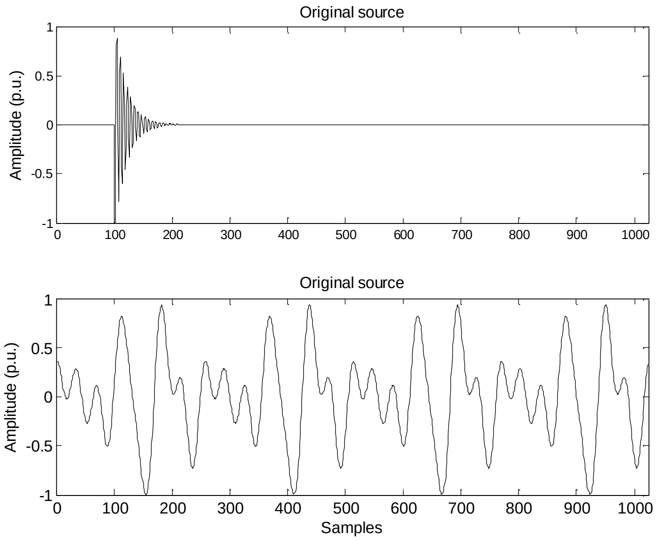
(b)

Fig. 5. Normalized estimated (a) and original (b) sources for the notch and harmonic disturbances.

Like most classification methods, the neural network was preceded by two stages: (i) feature extraction and (ii) feature selection. These stages were based on the HOS-based method proposed in [21], where higher-order statistics (HOS) (the diagonal slices of second and fourth order cumulants [22]) were used for feature extraction. For feature selection, the Fisherôs Discriminant Ratio (FDR) [23] was used, aiming at choosing a representative and finite set of features among those obtained by HOS that provides a good separability among the distinct classes and are robust to Gaussian noise.



(a)



(b)

Fig. 6. Normalized estimated (a) and original (b) sources for the capacitor switching and harmonics disturbances.

The simulated data were generated with 1,024 samples (4 fundamental cycles) and the sampling rate was f_s = 15,360 Hz. After the Notch filtering, the last 512 samples of the signal $e(n)$ were discarded. Next, 8 parameters (5 fourth and 3 second order cumulants) were selected (by FDR) and fed into the neural network input nodes for classifier design. The neural network comprised 3 processing layers: an input layer with 8 nodes, 3 neurons in the hidden layer and 3 output nodes, each one assigned to a given disturbance class. Thus, during the operation phase, the output node with maximum value determines the disturbance class assigned to the incoming signal.

A total of 500 waveforms with both harmonics and notches disturbances and 500 waveforms with both harmonics and capacitor switching disturbances were generated. The original sources of each disturbance of these waveforms were used to design the classifier previously described. The simulated disturbances were generated according to the IEEE standards [17].

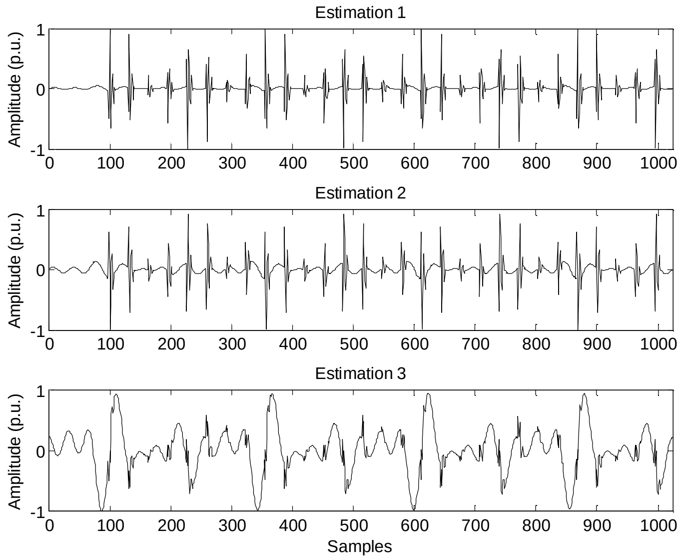


Fig. 7. Normalized estimated sources for the notch and harmonics disturbances.

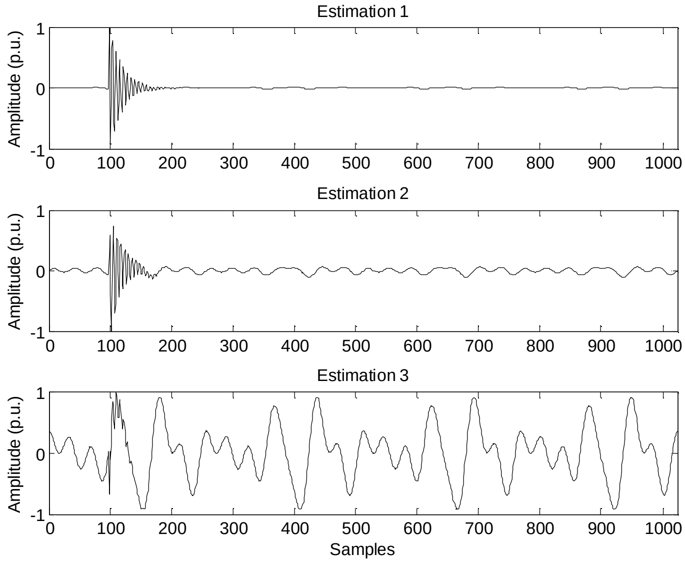


Fig. 8. Normalized estimated sources for the capacitor switching and harmonics disturbances.

Next, the multiple disturbance waveforms were presented to the proposed method (Fig. 2). First, the waveforms were partitioned into two signals ($x_1(n)$ and $x_2(n)$ or mixture 1 and mixture 2). The correlation coefficient between the original disturbance sources and the ICA estimated sources was used as a figure of merit for identifying which of the ICA estimations corresponds to harmonics or capacitor switching (or harmonics or notch disturbances, according to the mixture). Then, 500 ICA estimations of the notches, 500 of the capacitor switching and 1,000 of the harmonics were obtained. From the 1,000 harmonics estimations, 500 were related to the harmonics from the harmonic and notch mixture and the other 500 were related to the harmonics from the harmonic and capacitor switching mixture. Finally, these ICA estimations were pre-processed (feature extraction) and presented to the neural network. The underdetermined case was also considered, where the multiple disturbance waveforms were partitioned into three signals ($x_1(n)$, $x_2(n)$ and $x_3(n)$ or mixture 1, mixture 2 and mixture 3). A similar procedure to the two mixture case was applied.

Table I summarizes the achieved results. It can be seen that a good performance was obtained, especially for the notches and capacitor switching classes. Through these results, the accuracy of the proposed method for the multiple disturbances separation could be verified, considering that a classification system designed using original sources of single disturbances could classify the estimated sources by ICA-based proposed method with high efficiency.

TABLE I. CLASSIFICATION EFFICIENCIES IN %.

Disturbances	Using two mixtures	Using three mixtures
Harmonics from the mixture with notch	99.4	99.2
Harmonics from the mixture with capacitor switching	97.0	98.6
Notches	100	100
Capacitor Switching	99.8	100

To evaluate the performance of the proposed ICA-based method to decouple multiple disturbances in real world measurements, the experimental measurements shown in Figure 1 were presented to the proposed system. Figures 9 and 10 show the ICA estimated sources from the waveform voltage shown in Figure 1 (a), for two and three mixtures, respectively. Figures 11 and 12 show the ICA estimated sources from the waveform voltage shown in Figure 1 (b), for two and three mixtures, respectively.

Analyzing the estimated sources from the real world signals measurements, it is possible to verify the occurrence of each disturbance listed in Section II more clearly than only by analysis of their own waveforms voltage. In Figure 9, the harmonics appear clearly in estimation 2, and in Figure 10 these appear clearly in estimation 3. Short-transient intervals can be shown clearly in estimation 1 of Figure 10. In estimation 1 of Figure 12, the transients with decaying oscillation appear more clearly than in Figure 11 and the harmonics roughly appear in Figures 11 and 12 in estimations 2 and 3 respectively. These results show the efficiency of the ICA-based proposed method when applied to real data.

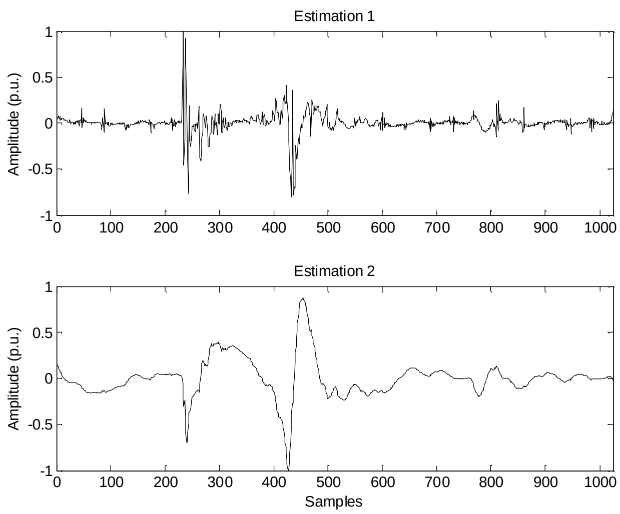


Fig. 9. Normalized estimated sources for the waveform voltage shown in Fig. 1 (a).

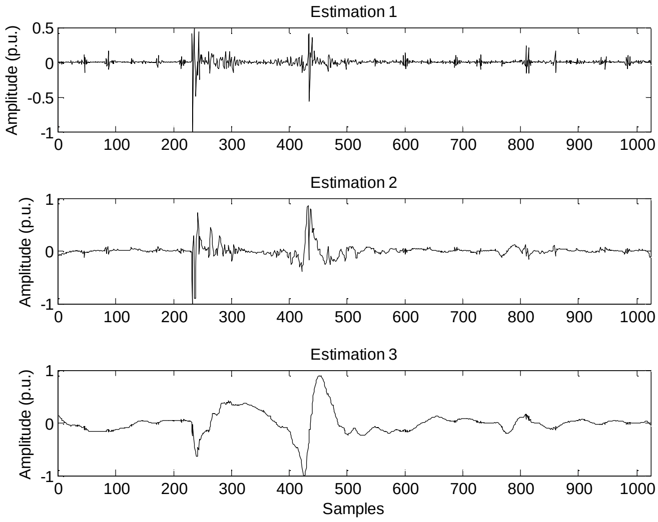


Fig. 10. Normalized estimated sources for the waveform voltage shown in Figure 1 (a) using three mixtures.

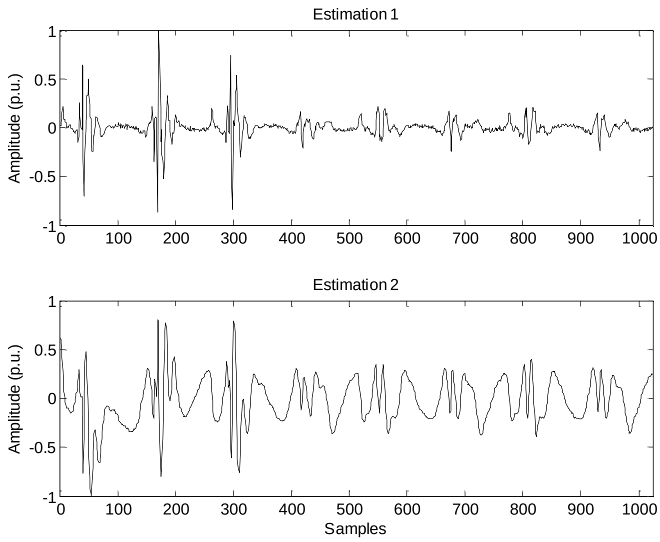


Fig. 11. Normalized estimated sources for the waveform voltage shown in Figure 1 (b).

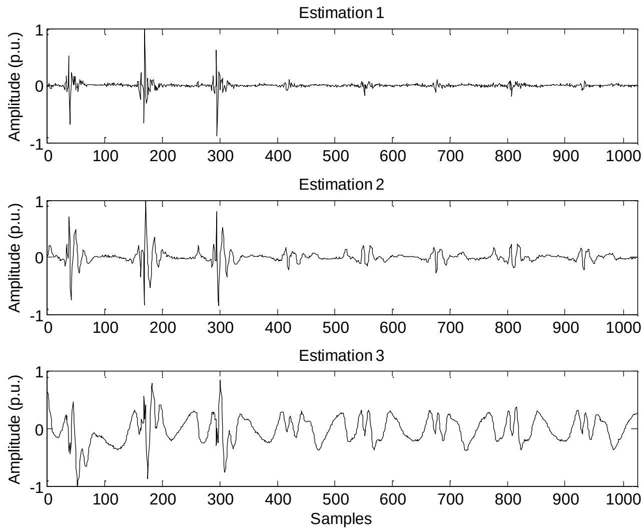


Fig. 12. Normalized estimated sources for the waveform voltage shown in Figure 1 (b) using three mixtures.

VI. Conclusions

In this paper, a new method for PQ multiple disturbances analysis, based on the ICA technique, was presented. This method was able to decouple the information between independent disturbance sources for simulated and experimental data.

The results from simulated data reveal that the ICA is capable of separating the occurrence of the multiple PQ disturbances considered in this paper using only one monitored device. As far as classification is concerned, the ICA source estimation is good enough, producing high classification efficiency.

The analysis of real world voltage disturbances shows that the proposed technique is attractive for application in power systems, where the occurrence of multiple disturbances is not rare.

VII. Acknowledgments

The authors would like to thank CNPq, CAPES, FAPEMIG and FAPERJ for their support to this work.

VIII. References

[1] W. G. Morsi and M. E. El-Hawary, ñA New Perspective for the IEEE Standard 1459-2000 Via Stationary Wavelet Transform in the Presence of Nonstationary Power Quality Disturbanceò, *IEEE Transactions on Power Delivery*, vol. 2, no. 4, pp. 2356 ï 2365, October 2008.

[2] M. H. J. Bollen, I. Y. H. Gu, S. Santoso, M. F. Mcgranaghan, P. A. Crossley, M. V. Ribeiro, P. F. Ribeiro, ñBridging the gap between signal and powerò, *IEEE Signal Processing Magazine*, vol. 26, no. 4, pp.12-31, 2009.

[3] S. Mishra, C. N. Bhende and B. K. Panigrahi, ñDetection and Classification of Power Quality Disturbances Using S-Transform and Probabilistic Neural Networkò, *IEEE Transactions on Power Delivery*, vol. 23, no. 2, pp.280 ï 287, January 2008.

[4] A. M. Gargoom, N. Ertugrul and W. L. Soong, ñAutomatic Classification and Characterization of Power Quality Eventsò, IEEE Transactions on Power Delivery, vol. 23, no. 4, pp. 2417 ï 2424, October 2008.

[5] F. Zhao, R. Yang, ñPower-Quality Disturbance Recognition Using S-Transformò, *IEEE Transactions on Power Delivery*, vol. 22, no. 2, pp. 944 ï 950, April 2007.

[6] M. V. Ribeiro and J. L. R. Pereira, ñClassification of Single and Multiple Disturbances in Electric Signalsò, *EURASIP Journal on Advances in Signal Processing*, 2007.

[7] Whei-Min Lin, Chien-Hsien Wu, Chia-Hung Lin and Fu-Sheng Cheng, ñClassification of Multiple Power Quality Disturbances Using Support Vector Machine and One-versus-One Approachò, International conference on Power System Technology, Chongqing, pp. 1-8, 2006.

[8] A. Hyvärinen, J. Karhunen and E. Oja, *Independent Component Analysis*. John Wiley & Sons, 2001.

[9] M. A. A. Lima, D. D. Ferreira, A. S. Cerqueira, C. A. Duque, M. V. Ribeiro and J. M. de Seixas. ñSeparation and recognition of multiple PQ disturbances using independent component analysis and neural networksò, *13th International Conference on Harmonics and Quality of Power* ICHQP, Wollongong, NSW, pp. 1-6, 2008.

[10] http://grouper.ieee.org/groups/1159/3/docs.html.

[11] A. Hyvärinen and M. Inki, ñEstimating Overcomplete Independent Component Bases for Image Windowsò, Journal of Mathematical Imaging and Vision, vol. 17, no. 2, pp. 139 ï 152, 2002.

[12] M. Borschbach and I. Hahn, ñSeparation capability of overcomplete ICA approachesò. *In Proceedings of the 6th Conference on 6th WSEAS international Conference on Signal Processing*, Dallas, Texas, vol. 6, pp. 146-151, 2007.

[13] F. J. Theis, E. W. Lang and C. G. Puntonet, ñA Geometric algorithm for Overcomplete Linear ICAò, *International Journal of Neurocomputing*, vol. 56, pp. 381-398, 2004.

[14] A. Hyvärinen, ñFast and robust fixed-point algorithms for independent component analysisò, *IEEE Transactions on Neural Networks*, vol. 10, no. 3, pp. 626-634, May 1999.

[15] M. Karimi-Ghartemani and M. R. Iravani, ñA nonlinear adaptive filter for online signal analysis in power systems: Applicationsò, *IEEE Transactions on Power Delivery*, vol. 17, no. 2, pp. 617-622, April 2002.

[16] S. K. Mitra, *Digital Signal Processing: A Computer-Based Approach*. McGraw-Hill, 1998.

[17] *IEEE Standards Coordinating Committee 22 on Power Quality*, IEEE recommended practice for monitoring electric power quality, Tech. Rep., IEEE, 1995.

[18] S. Haykin, Neural networks and Learning Machines, 3nd ed., NJ: Englewood Cliffs, Prentice Hall, 2008.

[19] D. Nguyen and B. Widrow. ñImproving the learning speed of 2-layer neural networks by chossing initial values of the adaptive weightsò, *IJCNN International Joint Conference on Neural Networks*, vol. 3, pp. 21ï26, 1990.

[20] M. Riedmiller and H. Braun. ñA direct adaptive method for faster backpropagation learning: The RPROP algorithmò, *In Proc. of the IEEE Intl. Conf. on Neural Networks*, San Francisco, CA, pp. 586-591, 1993.

[21] D. D. Ferreira, A. S. Cerqueira, C. A. Duque and M. V. Ribeiro, ñHOS-based method for classification of power quality disturbancesò, *Electronics Letters*, vol. 45, pp. 183-185, 2009.

[22] J. M. Mendel, ñTutorial on higher-order statistics (spectra) in signal processing and system theory: theoretical results and some applicationsò, *Proceedings of the IEEE*, vol. 79, no. 3, pp. 278-305, Mar. 1991.

[23] R. O. Duda, P. E. Hart and D. G. Stork, *Pattern Classification*, 2nd Edition, John Wiley & Sons, 2001.

IX. Biography

Danton Diego Ferreira received the B.S. degree in Electrical Engineering in 2005, and the M.Sc. degree in 2007. Since 2007, he has been a D.Sc. Student at the UFRJ/COPPE, Brazil. Since 2009, he has been an Assistant Professor at the Federal University of Lavras (UFLA), Brazil. His research interests are power quality analysis, computational intelligence and digital signal processing.

José Manoel de Seixas received the B.S. and D.Sc. degrees in electrical engineering, in 1979 and 1994, respectively. He has been an Associate Professor at the Electrical Engineering Department of Federal University of Rio de Janeiro, Brazil, since 1987. His research interests include computational intelligence, pattern recognition and instrumentation.

Augusto Santiago Cerqueira received the B.S. and D.Sc. degrees in 1998 and 2000, respectively. He has been an Associate Professor at the Electrical Engineering Department of Federal University of Juiz de Fora, Brazil, since 2004. He is presently working with instrumentation, digital signal processing and power quality issues.