Electric Power Systems Research 155 (2018) 274–280

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Voltage sag and swell detection and segmentation based on Independent Component Analysis

Erick A. Nagata [a], Danton D. Ferreira [a,*], Carlos A. Duque [b], Augusto S. Cequeira [b]

[a] *Engineering Department, Federal University of Lavras, Minas Gerais, Brazil*
[b] *Electrical Engineering Department, Federal University of Juiz de Fora, Minas Gerais, Brazil*

ARTICLE INFO

Article history:
Received 29 June 2017
Received in revised form 26 October 2017
Accepted 30 October 2017

Keywords:
Power quality
Voltage sag detection
Voltage sag segmentation
Independent Component Analysis

ABSTRACT

In this paper, a new method for voltage sag and swell detection and segmentation, based on Independent Component Analysis, is presented. The proposed method uses single channel ICA (SCICA) to blindly design suitable filters for sag and swell detection and segmentation, even in the presence of power quality disturbances such as sinusoidal voltage fluctuation, fundamental frequency variations, harmonics and phase-angle-jump. The performance of the proposed method was evaluated for both synthetic and real signals, in which the beginning and ending times of sags and swells were accurately detected. Moreover, the results were compared with a Wavelet-based method, showing that the performance of the proposed ICA-based method was better than the Wavelet one. The proposed method also showed to be robust to noise and frequency variations.

1. Introduction

Power Quality (PQ) analysis and monitoring has become a very active research area since the impact and losses caused by pour PQ cannot be neglected, mainly in industry, where pour PQ can cause equipment malfunction and manufacturing stoppage [1]. In this scenario, voltage sags and voltage swells are among the most common PQ disturbances. Sags can be caused by short-circuits occurred in the transmission or distribution network, start of large motor loads or switching operation associated with temporary disconnection of supply. Similar to sags, swells can be caused by system fault conditions, switching off a large load, load shedding or switching on a large capacitor bank [2].

Digital signal processing techniques are widely used in the context of Electric Power System, such as in Operation, Protection, Control and for PQ analysis and monitoring [1]. The Discrete Fourier Transform [3], Wavelet Transform [4] and Kalman Filters [5] are examples of techniques mostly used in the last decades. Therefore, PQ has increasingly demanded the development of new signal processing techniques.

Several signal processing techniques have been proposed for PQ disturbance detection and segmentation. In Ref. [6], sags, swells and interruptions are detected by RMS value. Its main drawback is the poor results achieved with non-stationary signals due to the dependency of the RMS on both periodicity and wave shape. A Sag/Swell detection algorithm based on wavelet transform, operating even in the presence of flicker and harmonics in the voltage source, is presented in Ref. [4]. In Ref. [5], Kalman Filter and an expert system is used to segment and identify different types of voltage dips (fault-induced, transformer saturation, induction motor starting) and interruption (nonfault and fault-induced). The main drawbacks of this method are related with either the failure in detecting very small changes in the voltage magnitude or the time resolution problems. In Ref. [7], it is presented a joint causal and anti-causal (CaC) segmentation method for automatic location of nonstationary parts of PQ disturbance. The authors use a cumulative sum algorithm and achieve accurately segmentation results. However, due to anti-causal approach, it is only valid for batch processing.

The IEC61000-4-30 [8] standard deals with detection and evaluation of voltage dips (sags) and swells. In this standard, the used method (RMS of a cycle, updated every half cycle) introduces half-cycle uncertainty in the detection of the beginning and ending of the event. In addition, the standard specifies that only the beginning, duration, and severity should be stored. Methods for detection-segmentation must be more accurate and must enable the detection of one disturbance within another one. These requirements are not yet standardized, and, therefore, new studies must be done when two or more disturbances are presented in the signal (multiple disturbances).

* Corresponding author.
E-mail addresses: eanagata@posgrad.ufla.br (E.A. Nagata), danton@deg.ufla.br (D.D. Ferreira), carlos.duque@ufjf.edu.br (C.A. Duque), augusto.santiago@ufjf.edu.br (A.S. Cequeira).

https://doi.org/10.1016/j.epsr.2017.10.029
0378-7796/

In this paper, a method based on Independent Component Analysis (ICA) [9] is developed envisaging the detection and segmentation of voltage sags and swells even in the presence of sinusoidal voltage fluctuation, harmonics and frequency variations. The proposed method uses the Single Channel ICA (SCICA) [10] approach, which is a specific case of the underdetermined one, wherein only one channel is analyzed. Using SCICA allows a simpler approach and has shown to be suitable for PQ disturbance analysis, as presented in the works reported in Refs. [11–13].

This work is an improved version of Ref. [14], which had some problems with false alarm. To overcome false alarm problems, the new proposed method has a different detection algorithm that improved considerably the detection results and allowed to include the segmentation capability. Moreover, the new version is a more complete work, with the addition of statistical and real signals analysis, more severe noise cases and deeper discussions.

2. Signal model

The discrete voltage signal version can be represented by a linear combination of fundamental component, disturbances and noise:

$$v[n] = v(t)_{t=\frac{n}{F_s}} := A[n]\cos\left[2\pi\frac{f[n]}{F_s}n + \phi[n]\right] + d[n] + r[n], \tag{1}$$

where $n = 0, \ldots, N-1$ is the sample index, F_s is the sampling frequency, $A[n]$, $f[n]$ and $\phi[n]$ refer to the magnitude, fundamental frequency, and phase of the fundamental component, respectively. $d[n]$ represents the PQ disturbance component that may be harmonics, sinusoidal voltage fluctuation and others, and $r[n]$ is the background noise.

According to Ref. [2], voltage sags and swells are characterized by voltage amplitude between 0.1 and 0.9 pu for sags, and between 1.1 and 1.8 pu for swells. The typical duration of such disturbances varies from 0.5 cycle to 1 min. To mitigate the problems caused by sags and swells, the first step is its detection and segmentation, which it is carried out in this work using Single Channel ICA [10].

3. Single channel ICA

The classic ICA model of an observed signal $\in R^N$ is a linear combination of statistically independent sources:

$$\mathbf{x}[n] = \mathbf{A}\mathbf{s}[n], \tag{2}$$

where $\mathbf{s}[n] = [s_1[n]s_2[n]\ldots s_M[n]]^T$ is a $M \times 1$ vector of statistically independent components (sources) at sample n, and $\mathbf{A}$ is a $M \times M$ matrix of weights called mixture matrix. If we assume the square matrix $\mathbf{A}$ invertible, then $\mathbf{s}[n] = \mathbf{W}\mathbf{x}[n]$, where $\mathbf{W} = \mathbf{A}^{-1}$ is called demixing matrix.

The ICA algorithms blindly estimate the original sources, meaning that the mixture matrix $\mathbf{A}$ in not known a priori. Therefore, the linear transformation should be found:

$$\hat{\mathbf{s}}[n] = \hat{\boldsymbol{W}}\boldsymbol{x}[n], \tag{3}$$

where $\hat{\mathbf{s}}[n] = \left[\hat{s}_1[n]\hat{s}_2[n]\ldots\hat{s}_M[n]\right]^T$ represents the vector of estimated independent components at sample n and $\hat{\boldsymbol{W}}$ is the estimated separation (demixing) matrix, which is an estimate of $\mathbf{A}^{-1}$.

In this work, Single Channel ICA (SCICA) [10] is used since only one observed signal is considered, which is a more realistic approach when considering PQ monitoring devices. The $s_i[n]$ components represent the sources present in the monitored voltage signal: disturbances, fundamental component and noise.

In order to apply the SCICA technique, a multi-channel representation is generated. This can be done by generating time-delayed versions from the observed discrete signal $x[n]$. Therefore, an embedded matrix is formed, composed by the observed signal and its delayed versions:

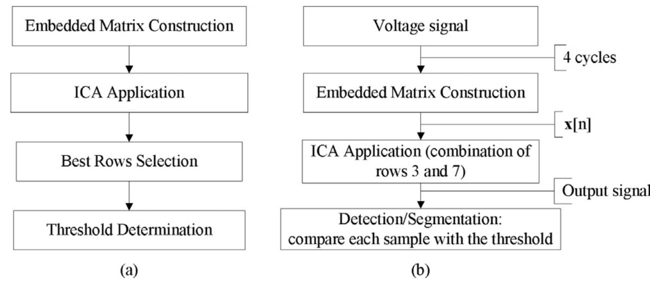

Fig. 1. Steps used in the design and operation stage of the proposed method. (a) Design. (b) Operation.

$$\mathbf{x}[n] = [x[n]x[n-1]\cdots x[n-M+1]]^T, \tag{4}$$

where $M = D+1$ is the number of lines of $\mathbf{x}[n]$ for D time-delayed versions of $x[n]$.

Among the algorithms that implement ICA, the SOBI algorithm was used in this work because it exploits the time information of the mixtures and presents robustness to noise [15].

4. Proposed method

In this section, the proposed method is described in detail.

4.1. Design

The design of the proposed method requires a specific data set, called development data set and can be divided into four steps. Fig. 1(a) presents these four steps in a block diagram of the design stage of the proposed method. In the design stage, the main goals are to find the separation rows of the demixing matrix $\mathbf{W}$ that highlight the voltage variations caused by sag and swell, and to determine the appropriate threshold to detect those variations.

Step 1: To construct the embedded matrix as (4), the number of delayed versions (D) of the monitored signal must be defined. Empirical tests using the development set were carried out envisaging the definition of D. The best results were found for $D = 15$. Therefore, the embedded matrix is composed of 16 rows, $D+1$.

Step 2: The second step is the application of the ICA algorithm in the embedded matrix $\mathbf{x}[n]$. In this work, we suggest the use of the SOBI [15] algorithm.

Step 3: The ICA algorithm returns a demixing matrix with 16 rows, but only a fraction of them leads to a good detection of sags and swells. For the dataset used in this work, it was verified that rows 3 and 7 led to better detection of sags and swells, therefore, the combination of both rows are used to achieve the system output.

Step 4: The system output signal is a filtered version of the input signal. Although the output does not preserve the input signal amplitude, it highlights the transient part of sags and swells. Therefore, the signal transients give the location of the disturbance, but it is necessary to determine a threshold for detecting these transients. From this, besides performing the detection of disturbances, its beginning and ending times are also determined, so the disturbance segmentation can be performed. Simulations were carried out with different disturbances and different values of noise (SNR = 40 dB, 50 dB and 60 dB) in order to define the suitable values of the threshold. It was observed that the noise amplitude in the output signal was smaller than 0.04 pu in about 99% of the development set. Thus, the chosen threshold for detection is 0.04 pu.