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A method based on independent component analysis for single and multiple power quality disturbance classification

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ABSTRACT

This paper proposes a method based on single channel independent component analysis for single and multiple power quality disturbance classification. The proposed method decouples the power system signal into its independent components, which are classified by specialized classifiers. The classifier outputs are combined by using a logic that gives the final classification. Five classes of single disturbances and twelve of multiple disturbances are considered and a classification efficiency above 97% is achieved for each event class. Both qualitative and quantitative analysis elucidate the efficiency of the proposed method. Results are obtained from both simulated and experimental signals.

1. Introduction

The quality of electric power has become an important issue for electric utilities and their customers. As a result, power quality study has become an active research area in the last few years [1]. Degradation in electric power quality is normally caused by disturbances such as voltage sag/swell with and without harmonics, harmonic distortion, notch, spike and transients, causing problems such as malfunctions, instabilities, short lifetime, failure of electrical equipments and so on.

In order to determine the causes and sources of disturbances, one must have the ability to detect and classify these disturbances. These process in blocks are required for correct disturbance identification before appropriate mitigating action can be taken. Recently, a bunch of methods have been proposed for the automatic recognition of the PQ disturbances, as reported in [1], however, most of them were proposed for recognizing single disturbances. Thus, the performance of these methods might be limited because, for many power networks, the disturbances may appear simultaneously and are commonly referred to as multiple disturbances.

Regarding the classification of multiple disturbances, many recent works have considered the occurrence of only two classes: sag with harmonics and swell with harmonics [2–4]. The authors in [5] have used ant colony optimization technique for disturbance classification in which four classes of multiple disturbances were considered: sag or swell with harmonics, flicker with harmonics and interruption with harmonics. The authors in [6] have used a S-transform variant and Fuzzy decision tree for classifying six classes of multiple disturbances: sag or swell with transient, swell with harmonics, harmonics with notch or flicker and spike with transient. In [7], sag or swell with harmonics, sag or swell with transient and sag or swell with flicker were combined allowing the classification of six classes of multiple disturbances by using fuzzy logic and particle swarm optimization. In [8], eight classes of multiple disturbances (sag or swell with transient, sag or swell with harmonic, sag or swell with flicker, flicker with harmonic and harmonic with transient) were considered for classification by using discrete wavelet transform and wavelet networks. These works have achieved good and promising results, however they are limited to a reduced number of multiple disturbance classes (up eight) and combining only two types of single disturbances.

In the present paper, a method based on single channel independent component analysis (SCICA) is proposed to analyze and classify PQ events with multiple disturbances, following the idea first proposed in [9]. In [9] the authors introduced the SCICA method to decompose and classify two classes of multiple disturbances:

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harmonics with oscillatory transients and harmonics with notches. Here, the use of a simplified version of the SCICA method [10] is proposed for decoupling multiple disturbances allowing the classification of a great number of single and multiple disturbance classes.

According to [11], the discrete version of power line signals can be expressed as an additive contribution of several types of phenomena, say: fundamental component, harmonics, interharmonics, transient and noise. From this, the processing target is to decouple the multiple disturbances into single ones. This is the case of independent component analysis (ICA) [12], which, in this context, aims at separating blindly the original disturbance sources that built the acquired voltage signal. The ICA is a well-known blind source separation technique and has been applied in different fields [12]. The proposed methodology is applied through monitoring only a single power line and, therefore, the so called single channel ICA (SCICA) [10] method is employed.

2. Single channel ICA

According to [10], the SCICA approach refers to an extreme case of underdetermined ICA (one sensor), and it is an instance of multidimensional independent component analysis applied to vectors of delayed samples. In other words, to apply ICA to a single channel it is first necessary to form a 'multi-channel' representation. This can be done by generating a series of delayed vectors taken from the observed signal $x[n]$:

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

where $n = 1, \ldots, N$ is the number of samples, T superscript denotes transposition and $M \times N$ is the order of $\mathbf{x}[n]$, so that M is given by the number of time-delayed versions of the observed signal to be used plus one (the observed signal). Thus, the basic formulation of the ICA may be recovered, such as

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

where $\mathbf{s}[n] = [s_1[n], s_2[n], \ldots, s_M[n]]^T$ is the $M \times N$ statistically mutually independent component matrix at sample n that forms the observed signal (i.e. $s_i[n]$ is the source vector) and $\mathbf{A}$ is a $M \times M$ scalar matrix that performs the mixture of sources. This matrix is called mixing matrix.

The ICA algorithms estimate the original source signals blindly, i.e., using only the observed signals [12]:

$$\mathbf{y}[n] = \mathbf{W}\mathbf{x}[n]. \tag{3}$$

In this equation, $\mathbf{y}[n] = [y_1[n], y_2[n], \ldots, y_M[n]]^T$ is the estimated source matrix and $\mathbf{W}$ is the de-mixing matrix estimated by the ICA algorithm ($\mathbf{W} = \mathbf{A}^{-1}$).

There are several approaches to obtain the separation matrix $\mathbf{W}$ from mixtures using certain statistical properties of the source signals such as non-Gaussianity, temporal structure, cross-cumulants and non-stationary [12]. From these properties, several algorithms have been proposed in the literature. In this work, the second order blind identification (SOBI) algorithm [13] is used, once it exploits temporal information of the mixtures.

In such a multi-dimensional model, sources can only be successfully identified and separated using ICA when they have disjoint spectral information, as proved in [10]. Then, when ICA is applied to delayed vectors formed from a mixture of bandlimited sources, it will identify a multiple number of components with each source proportional to the source bandwidth. The column vectors of $\mathbf{A}$ associated with a given source can be interpreted as shifted versions of a mixing finite impulse response (FIR) filter and the row vectors of $\mathbf{W}$ are the shifted versions of the de-mixing FIR filter, which will finally obtain the estimated sources $y_i[n]$.

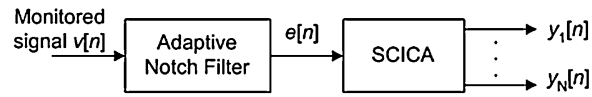

Fig. 1. Block diagram of the proposed method in the design phase.

In summary, the estimate of each independent component can be obtained by one of the filtered versions of the mixture $x[n]$, where the coefficients of each FIR filter are given by the rows of the de-mixing matrix $\mathbf{W}$, or by grouping together signals with the same spectral content. In [10], signals with the same spectral information are grouped using the k-means algorithm. Unlike [10], we propose to use the rows of $\mathbf{W}$ as filters to decompose the multiple disturbances, avoiding thus grouping task, which leads to a simpler approach.

3. Proposed ICA-based method

The design of the proposed method for multiple disturbance decomposition can be basically split into two blocks, as it is displayed in Fig. 1. The first stage comprises an adaptive notch filter employed for removing the fundamental component (60 Hz here) of the power system voltage signal $v[n]$. Thus, the remaining signal after applying the first stage contains only PQ disturbance information, except for the sags and swells, which are PQ disturbances related to the fundamental component.

The adaptive notch filter structure used is EPLL (enhanced phase locked-loop), as proposed in [14]. The EPLL provides three advantages, when compared to a classical notch filter topology: (i) no phase difference between the estimated fundamental component and 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 frequency.

The output of the filter, here named $e[n]$, is then presented to the SCICA method, which finally obtains the independent components ($y_i[n]$, for $i = 1, \ldots, M$). Hence, the most important task of the design stage is to analyze these independent components in order to identify which of them represents better the original disturbance source. The rows of the achieved de-mixing matrix $\mathbf{W}$ that correspond to the better disturbance estimations are chosen. Thus, in the operational stage, each disturbance source is obtained by

$$\mathbf{y}_i = \mathbf{w}_i \mathbf{x}[n], \tag{4}$$

where $\mathbf{y}_i$ is the sample vector of the estimated single disturbance i, $\mathbf{x}$[n] is the observed time-delay matrix, which is formed by the monitored signal $e[n]$ and its time-delayed versions according to (1), and $\mathbf{w}_i$ is the chosen row.

The last stage of the design system consists in defining how many time-delayed versions of the signal $e[n]$ are required to provide a good estimation of the disturbance source. Actually, the quality of estimated sources is related to the number of time-delayed versions of the observed signal. Biomedical applications [10] use a large number of delayed versions, about 100, while for the application here proposed, it was found that just three delayed versions provide good results.

Thus, in the operational stage, the disturbance sources are obtained by the linear combination between the elements of the vector $\mathbf{w}_i$ and the rows of the observed time-delay matrix, avoiding the use of the algorithm ICA, which is applied only in the design phase, and the use of clustering techniques.