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Rule-based classification of power quality disturbances using S-transform

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ABSTRACT

This paper presents a rule-based approach for the classification of power quality disturbances. The disturbed signal is first characterized using the multi-resolution S-transform, which acts as a feature extraction tool. Then, a simple but robust rule-based classification algorithm is used to identify disturbances. This algorithm uses linear and parabolic rules as pattern classifiers where decision boundaries are established by a heuristic search. The classification algorithm has a modular structure where each module works separately to detect specific disturbances.

The most common types of disturbances, including sags, interruptions, swells, harmonics and oscillatory transients, were analyzed. Moreover, complex disturbances consisting of combinations of two simple events (simultaneous or consecutive in the same interval) were also analyzed. In both cases, noise, ranging from 40 to 20 dB, was also considered. The tested data set contains power quality signals obtained using mathematical models, power quality events obtained from power network's simulations using PSCAD/EMTDC and measured signals at electrical installations.

Finally, evaluation results verifying the accuracy of the proposed method are presented and compared to those obtained from a classification system based on an artificial neural network.

1. Introduction

Regular operations in the distribution network, such as switching loads and capacitors, fault clearing and lightning, along with the proliferation of power electronic equipment and non-linear loads in industrial, commercial and domestic applications, have led to increased amounts of polluted power systems in terms of distorted voltage and current signals. These distortions can lead to failures or malfunctions of the many sensitive loads connected to the power system, thus incurring a high cost for end users. Several studies quantify these costs in modern power systems [1,2]. Improvement of power quality (PQ) standards has a positive impact not only on the distribution utility but also on PQ-sensitive energy customer satisfaction. PQ is becoming increasingly important and is widely recognized as one of the major issues to be addressed in modern power systems [2].

One major requirement to ensure power quality in distribution systems is the monitoring of power system performance. PQ monitoring is not an easy task, and it typically involves sophisticated hardware instrumentation and software packages. A key point in this task is the analysis of large amounts of monitored data with minimum intervention from PQ experts [3]. Therefore, it is desirable to develop expert-based tools for automatic analysis and classification of PQ events.

A number of techniques have been proposed for automated classification of different types of PQ events [4–21]. These approaches share a common working scheme, which is depicted in Fig. 1. Monitored signals are first filtered using some type of signal processing tool for feature extraction. Then, distinctive features are fed into a previously trained classifier module for identification and classification.

In this work, the general scheme proposed in Fig. 1 has been followed. For the distorted signals, several sources have been considered: (i) synthetic signals obtained from parametric equations, (ii) signals generated by network simulation using PSCAD/EMTDC [22], and (iii) measured signals at electrical installations. These groups of signals contain most typical simple disturbances, including sags, interruptions, swells, harmonics and oscillatory transients, as well as complex disturbances consisting of combinations of two simple simultaneous or consecutive events in the same interval.

The pattern extraction phase consists of the identification of characteristics that facilitate joint distinctive patterns belonging to each perturbation group that are immune to noise and easy to obtain and interpret. There exists no general approach for feature selection; this strongly depends on expertise knowledge [23].

In PQ analysis, many approaches make use of signal processing tools to extract distinctive features. Among existing signal processing tools, the Fourier transform (FT) is inadequate for analysis of non-stationary events, and the short-time Fourier transform (STFT), although to a lesser extent, also fails to achieve good resolution in both time and frequency. On the other hand, time-frequency transforms such as the wavelet transform (WT) have also been used in

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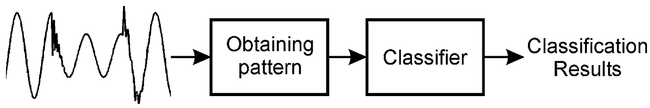

Fig. 1. Automated classification scheme.

PQ studies [4–12]. The WT extracts information from the signal in the time and frequency domains simultaneously. However, it also exhibits some disadvantages, such as sensitivity to noise level and dependency of its accuracy on the selected basis wavelet.

More recently, the S-transform (ST) has been proposed in PQ analysis to overcome the drawbacks of the WT [13–21]. The ST can conceptually be interpreted as a hybrid of the STFT and the WT. It uses variable window length and, through use of the FT kernel, can preserve phase information during decomposition [24]. In this work, extracted features from distorted signals are obtained using the ST. It is shown that even in the presence of complex disturbances with different levels of noise this tool successfully characterizes the signals.

Finally, a classifier must be designed. Most of the artificial intelligence techniques have been used as classifiers in PQ analysis. They have been combined with the WT or ST, such as in artificial neural networks (ANNs) [5–7,14–16], fuzzy logic [8,17], decision trees [9,18], hidden Markov models [12], support vector machines [10,19], and expert system [12,20,21].

The main highlights at every single stage represented in Fig. 1 are the following:

- As an extension to previous works [9,10,13–21] where it is only analyzed complex disturbances consisting of combinations of sag and harmonics and swell and harmonics, we have also analyzed some other plausible complex perturbations such as sag and transient oscillation, swell and transient oscillation, and, finally, transient oscillation and harmonics. This new perturbations clearly introduce higher complexity in the data set. Noise ranging from 40 to 20 dB has also been considered.
- A reduced and simple set of features extracted from the S-transform are associated to each distorted signal class enabling the classifying stage. This allows advancing in accuracy, simplicity and reliability.
- The development of a rule-based classifier consisting of several units, each of which is specialized for one type of disturbance and only makes use of the proposed features that are necessary for its function. These units work separately such that the whole system can easily detect complex disturbances.

This paper is organized as follows. In Section 2, the development of the basic theory of multi-resolution ST is briefly described and is used to obtain distinctive features for classification. The rule-based classifier design is described in Section 3. Classification results using synthetic, simulated and measurement signals are presented in Section 4. These results are compared with those obtained from a system based on a feedforward backpropagation ANN. Finally, conclusions are presented in Section 5.

2. Pattern design using the S-transform

2.1. Mathematical formulation

The ST [24] was introduced as an alternative to the STFT for localization of time–frequency spectra. The ST gives time and frequency information, as does the STFT, but it uses a variable window length that provides information at different resolutions, such as in the case of the WT [24].

The ST can be derived from the WT by modifying the phase of the window function or mother wavelet. Given a time-dependent signal, $x(t)$, the ST can be derived [24] as the product of the signal and a phase correction function $e^{(-j2\pi f\tau)}$.

The S-transform of $x(t)$ is defined as:

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t) g_f(\tau - t) e^{-j2\pi f t}\, dt \tag{1}$$

where $g_f(\tau)$ is the Gaussian modulation function, defined as:

$$g_f(\tau) = \frac{|f|}{\sqrt{2\pi}} e^{-(\tau^2/2\sigma^2)} \tag{2}$$

and

$$\sigma = \frac{1}{|f|} \tag{3}$$

The expression becomes:

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-((\tau - t)^2 f^2/2)} e^{-i2\pi f t}\, dt \tag{4}$$

The discrete version of (4) is calculated, taking advantage of the efficiency of the fast Fourier transform. The discrete Fourier transform of the time series $x(t)$ is obtained as:

$$H\left[\frac{n}{NT}\right] = \sum_{k=0}^{N-1} x(kT) e^{-(2\pi i/N)nK} \tag{5}$$

The discrete S-transform is obtained by allowing $f \rightarrow n/NT$ and $\tau \rightarrow jT$:

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left(\frac{m+n}{NT}\right) G(m, n) e^{i2m\pi j/N} \tag{6}$$

where

$$G(m, n) = e^{-2\pi^2 m^2/n^2} \tag{7}$$

and $j, m, n = 0, 1, \ldots, N-1$.

The discrete inverse of the S-transform can be obtained as:

$$x(kT) = \sum_{n=0}^{N-1} \left[\sum_{j=0}^{N-1} S\left(jT, \frac{n}{NT}\right) \right] e^{i2nk} \tag{8}$$

The output from ST analysis is a complex matrix whose rows and columns represent frequency and time, respectively. Each column represents the local spectrum in time. Frequency–time contours with the same amplitude spectrum are also obtained. This information is used to detect and characterize power disturbance events.

An example of a multi-resolution ST analysis for a complex signal containing an oscillatory transient and a 7th harmonic is presented in Fig. 2. The perturbed signal is plotted in the time domain in Fig. 2(a). In Fig. 2(b), the manner in which these two disturbances are located in a time–frequency domain can also be observed. Finally, in Fig. 2(c), a 3-D mesh showing amplitude, frequency and time plots where, for the sake of clarity, the values associated with the fundamental frequency have been omitted is depicted.

2.2. Distinctive features

The accuracy of the classification depends not only on the number of distinctive features but also on the characteristics of these features that make them unique and salient. An efficient pattern can be defined from the observation of ST contours. Below, some examples of signals with various disturbances are analyzed in order to illustrate the pattern proposed in this approach.