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An expert system based on S-transform and neural network for automatic classification of power quality disturbances

Murat Uyar [a,*], Selcuk Yildirim [a], Muhsin Tunay Gencoglu [b]

[a] Department of Electric Science, Firat University, 23119 Elazig, Turkey
[b] Department of Electrical and Electronics Engineering, Firat University, 23119 Elazig, Turkey

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ABSTRACT

In this paper, an S-transform-based neural network structure is presented for automatic classification of power quality disturbances. The S-transform (ST) technique is integrated with neural network (NN) model with multi-layer perceptron to construct the classifier. Firstly, the performance of ST is shown for detecting and localizing the disturbances by visual inspection. Then, ST technique is used to extract the significant features of distorted signal. In addition, an optimum combination of the most useful features is identified for increasing the accuracy of classification. Features extracted by using the S-transform are applied as input to NN for automatic classification of the power quality (PQ) disturbances that solves a relatively complex problem. Six single disturbances and two complex disturbances as well pure sine (normal) selected as reference are considered for the classification. Sensitivity of proposed expert system under different noise conditions is investigated. The analysis and results show that the classifier can effectively classify different PQ disturbances.

1. Introduction

Power supply quality issues and the resulting problems are the consequences of increasing use of solid state switching devices, non-linear and power electronically switched loads, unbalanced power systems, lighting controls, computer and data processing equipments as well as industrial plant rectifiers and inverters. These electronic type loads cause voltage distortion, inrush, pulse type current phenomenon with excessive harmonics and high current distortion (Dugan, McGranaghan, Santoso, & Beaty, 1996). A power quality (PQ) problem usually involves a variation in the electric service voltage or current, such as voltage sag/swells, momentary interruptions, fluctuations, harmonics and oscillatory transients causing failure or mal-operation of sophisticated electronic equipment.

In order to improve PQ, the sources and causes of such disturbances must be known before appropriate mitigating actions can be taken. A feasible approach to achieve this goal is to incorporate detection capabilities into monitoring equipment so that events of interest will be recognized, captured, and classified automatically. Hence, good performance monitoring equipment must have functions which involve the detection and classification of transient events. In particular, when the disturbance type has been classified accurately, the major effects of the disturbance at the load can be defined so that a convenient solution can be implemented (Gaing, 2004).

Artificial neural network (ANN) systems can provide an effective method to cope with such problems (Gaouda, Salama, Sultan, & Chikhani, 1999; Santoso, Powers, Grady, & Parsons, 2000). However, the complexity of the classifier structure may depend on the choice of the feature parameters as well building the ANN system. Therefore, an effective signal processing technique must be offer for analyzing PQ related problems.

In literature, the signal processing techniques are available for analyzing PQ disturbance. Some examples are sort time Fourier transform (STFT) method Heydt et al. (1999), fractal-based method Huang and Hsieh (2001), time–frequency ambiguity plane method Wang, Ochenkowski, and Mamishev (2001), discrete wavelet transform (DWT) method (Gaouda et al., 1999; Santoso et al., 2000), and S-transform (ST) method (Dash, Chilukuri, & Panigrahi, 2003).

As PQ disturbances are non-stationary signals, the most important requirement is to extract useful features from the signal. For feature extraction from non-stationary signal, STFT, DWT and ST has been used extensively. STFT performs satisfactorily for stationary signals where properties of signals do not change in time. For non-stationary signals, the STFT does not track the signal dynamics properly due to the limitations of a fixed window width chosen a priori (Xu, Senroy, Suryanarayanan, & Ribeiro, 2006). On the other hand, wavelet transform provides a unified framework for monitoring PQ problems.

* Corresponding author. Tel.: +90 424 2370000x4304; fax: +90 424 2367064.
E-mail address: muyar@firat.edu.tr (M. Uyar).

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The DWT is based on the decomposition of a signal according to time-scale, rather than frequency, using basis functions with adaptable scaling properties. A wavelet transform expands a signal not in terms of a trigonometric polynomial but by wavelets, generated using transition and dilation of a fixed wavelet function called the "mother wavelet". The wavelet function is localized in time and frequency yielding wavelet coefficients at different scales (Daubechies, 1992). This gives the wavelet transform much greater compact support for analysis of signals with localized transient components arising in PQ disturbances manifested in voltage, current or frequency deviations. Several types of wavelets have been considered for detection, localization, and classification of PQ problems as both time and frequency information is available by multiresolution analysis (Gaouda et al., 1999). Although wavelet multiresolution analysis combined with a large number of neural networks provides efficient classification of PQ disturbances, the time-domain featured disturbances, such as sags, swells, etc. may not easily be classified. In addition, the frequency properties of the decomposition filter bands are not ideal and suffer leakage effects where the signal frequency is closer to the edge of a frequency band. Thus, some of the important disturbance frequency components are not extracted precisely by the DWT (Borras, Castilla, Moreno, & Montano, 2001). Therefore, a more suitable signal processing technique is considered in this paper for recognizing the voltage signal patterns.

The ST is an invertible time–frequency spectral localization technique that combines elements of WT and STFT (Pinnegar & Mansinha, 2003; Stockwell, Mansinha, & Lowe, 1996). The ST uses an analysis window whose width is decreasing with frequency providing a frequency-dependent resolution. The ST is a continuous wavelet transform with a phase correction. It produces a constant relative bandwidth analysis like wavelets, although maintains a direct link with Fourier spectrum. The ST has an advantage in that it provides multiresolution analysis while retaining the absolute phase of each frequency. This has led to its application for detection and interpretation of non-stationary signals. Further, the ST provides frequency contours which clearly localize the signals at a higher noise level. One of the advantages over WT of ST is to avoid the requirement of testing various families of wavelets to identify the best one for a better classification. The superiority of the ST over wavelet in classifying four types of PQ disturbances by visualizing the contour of ST (i.e., manual classification) has already been reported (Dash et al., 2003).

Automatic classification of PQ disturbances is still a difficult problem, because it involves a broad range of disturbance categories and varying degree of irregularities (Chilukuri & Dash, 2004). In this paper, an ST-based neural network classification process is presented for automatic classification of PQ disturbances. Moreover, the effectiveness of the ST is shown by visual inspection of PQ disturbances. To construct an effective classifier, it is essential to choose a suitable feature vector that can indicate and recognize the main characteristics of signal. For this purpose, the statistical features based on ST, the reduction of data size as well indicating and recognizing the main characteristics of signal without losing its distinguishing characteristics is extracted. In addition, the effectiveness of features is increased by selecting optimum feature combination with scatter plots. The automatic classification stage is implemented by using NN structure based on multi-layer perceptron with RPROP learning algorithm. The classification process is applied on a set of different PQ disturbances, such as voltage sag, voltage swell, momentary interruption, harmonic distortion, voltage sag with harmonic and oscillatory transient as well pure sine (normal) selected as reference. Sensitivity to noise of the presented schema is tested under different noise conditions. Analysis and results is shown that the classification process based on the ST may be used to classify typical PQ disturbances encountered in power systems.

The rest of this paper is organized as follow. In Section 2, definitions and concepts of the ST are introduced and the performance of ST is shown for detecting and localizing the disturbances by visual inspection. In Section 3, feature extraction and classification method used this study are given. In Section 4, simulation and analysis studies are presented and the classification results and performance comparison of proposed expert system are shown. Finally, conclusions are discussed in Section 5.

2. S-transform

2.1. Continuous S-transform

It is well known that information is contained both in the phase and amplitude spectrum. In order to utilize the information contained in the phase of the continuous wavelet transform (CWT), it is necessary to modify the phase of the mother wavelet. The CWT $W(\tau,d)$ of a function *y(t)* is defined as

$$W(\tau,d)=\int_{-\infty}^{\infty}y(t)w(t-\tau,d)\mathrm{d}t \tag{1}$$

The scale parameter d determines the width of the wavelet $w(t, d)$ and, this controls the resolution. The ST of a function *y(t)* is defined as a CWT with a specific mother wavelet multiplied by the phase factor

$$S(\tau,f)=\mathrm{e}^{\mathrm{i}2\pi f\tau}W(\tau,d) \tag{2}$$

where the mother wavelet for this particular case is defined as

$$w(t,f)=\frac{|f|}{\sqrt{2\pi}}\mathrm{e}^{-\frac{t^2f^2}{2}}\mathrm{e}^{-\mathrm{i}2\pi ft} \tag{3}$$

Note that the scale parameter d is the inverse of the frequency f. The wavelet in (3) does not satisfy the condition of zero mean for an admissible wavelet; therefore, (2) is not strictly a CWT. Thus, the final form of the continuous ST is obtained as (4)

$$S(\tau,f)=\int_{-\infty}^{\infty}y(t)\frac{|f|}{\sqrt{2\pi}}\mathrm{e}^{-\frac{(\tau-t)^2f^2}{2}}\mathrm{e}^{-\mathrm{i}2\pi ft}\mathrm{d}t \tag{4}$$

and the width of the Gaussian window is

$$\sigma(f)=T=\frac{1}{|f|} \tag{5}$$

The ST also can be written as operations on the Fourier spectrum *Y(f)* of *y(t)*

$$S(\tau,f)=\int_{-\infty}^{\infty}Y(\alpha+f)\mathrm{e}^{-\frac{2\pi^2\alpha^2}{f^2}}\mathrm{e}^{\mathrm{i}2\pi\alpha\tau}\mathrm{d}\alpha,\quad f\neq 0 \tag{6}$$

2.2. Inverse S-transform

Since ST is a representation of the local spectra, Fourier or time average spectrum can be directly obtained by averaging the local spectrums as

$$Y(f)=\int_{-\infty}^{\infty}S(f,\tau)\mathrm{d}\tau \tag{7}$$

$$y(t)=\int_{-\infty}^{\infty}\left\{\int_{-\infty}^{\infty}S(f,\tau)\mathrm{d}\tau\right\}\mathrm{e}^{\mathrm{i}2\pi ft}\mathrm{d}f \tag{8}$$

2.3. Discrete S-transform

The PQ disturbance signal *y(t)* can be stated in a discrete form as $y(k,T)$, where is the time sampling interval T and is the total sampling number N, $k = 0,1,\ldots,N-1$.