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Power quality time series data mining using S-transform and fuzzy expert system

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ABSTRACT

This paper presents a new approach for power quality time series data mining using S-transform based fuzzy expert system (FES). Initially the power signal time series disturbance data are pre-processed through an advanced signal processing tool such as S-transform and various statistical features are extracted, which are used as inputs to the fuzzy expert system for power quality event detection. The proposed expert system uses a data mining approach for assigning a certainty factor for each classification rule, thereby providing robustness to the rule in the presence of noise. Further to provide a very high degree of accuracy in pattern classification, both the Gaussian and trapezoidal membership functions of the concerned fuzzy sets are optimized using a fuzzy logic based adaptive particle swarm optimization (PSO) technique. The proposed hybrid PSO-fuzzy expert system (PSOFES) provides accurate classification rates even under noisy conditions compared to the existing techniques, which show the efficacy and robustness of the proposed algorithm for power quality time series data mining.
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1. Introduction

Data mining is one of the key areas which have extensive use in real world situations such as business, science, technology, government and academia. Data mining involves fitting models to or determining pattern from observed data. The fitted models play the role of inferred knowledge. Typically, a data mining algorithm constitutes a model, a preference criterion, and a search algorithm. The more common model functions in data mining include classification, clustering, rule generation and knowledge discovery.

The continued growth in data collection in all of these areas ensures that the fundamental problem of how does one understand and uses one's data, will continue to be of critical importance across a large number organizations. Although simple statistical techniques and machine learning for data analysis were developed long ago, advance techniques for intelligent data analysis are not yet mature [1–3]. Knowledge discovery can be regarded as one of the prime function of data mining that is a new generation of information processing technology.

Electrical power disturbance signals are considered as one of the similar time series data to be studied for time series pattern classification problems. In electrical power networks, the voltage and current signals exhibit fluctuations in amplitude, phase, and frequency due to the operation of solid-state devices that are prolifically used for power control. The sudden increase and decrease in voltage signal are known as swell and sag, respectively. If the signal amplitude momentarily becomes zero, it is the condition of interruption. Apart from these steady state disturbances, transient oscillations are seen in power networks when power electronically controlled capacitors are switched across a node in an electrical power network. These transients are of large amplitude in comparison to the normal voltage or current signal and exhibit multiple frequencies ranging from 300 Hz to 5000 Hz. In addition to oscillatory transients, impulsive transients, multiple voltage notches due to solid-state converter switching, harmonics, and power sinusoids being modulated by low frequency signals are also observed in the electric power networks. To distinguish between the various power quality disturbance signal patterns like sag, swell, oscillatory transients, impulsive transients, notch, and the normal sinusoidal signals of frequency 50 Hz or 60 Hz, advanced signal processing techniques along with intelligent systems approach play a very important role in generating patterns that resemble the nature of the non-stationary disturbance.

Existing automatic recognition methods for time-series pattern classification need improvement in terms of their capability, reliability, and accuracy. Approaches for automated detection and classification of time-series data, proposed recently are based on wavelet analysis, artificial neural networks, hidden Markov models, time frequency ambiguity planes, etc. [4–12]. These techniques have been successfully employed in other pattern recognition and signal processing applications, such as speech recognition, audio

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processing, communications, and radar and sonar applications, where the data is found to be a non-stationary time series.

Although the above-mentioned techniques provide improved recognition rates, they are not yet sufficient for supporting a robust data mining algorithm. Among the suitable algorithms for non-stationary time-series data such as power system disturbance signals waveform processing, the wavelet is found to be most efficient since its multiresolution decomposition contains time domain information of the signal at different scales. Although wavelets are a promising tool for detecting and extracting relevant features of various types of non-stationary time series data, they are still not optimal since they are a set of band pass filters with no exact cut off frequency. Besides wavelet-based methods require more training examples a large number of neural networks for pattern classification.

The S-transform [13] has an advantage in that it provides multiresolution analysis while retaining the absolute phase of each frequency. S-transform can be regarded as a variable window short-time Fourier transform and has superior pattern recognition characteristics in the presence of random noise. This has led to its application for detection and interpretation of time series events in a variety of disciplines. Some examples are analysis of the time variation in the amplitude and phases of sea level data in oceanography, analysis of seismic waveform and electrocardiogram data in cardiology, power quality disturbance data. For power quality data mining, sampled voltage and current signals are processed by using a multiresolution transform S-transform to extract relevant features. The extracted features bear the signatures of different power quality time series events, and hence are combined with a variety of pattern classifiers such as rule-based system [14,15], K-nearest neighbor classifier [16], artificial neural networks (ANN) [17,18], support vector machines [19,20], fuzzy logic based systems [21,22] to classify power quality events. Without these features neural, fuzzy, and other classifiers cannot recognize the time series events on their own using the raw data from the power networks. Most of these classifiers require elaborate training and may lead to inaccuracies with insufficient and noisy data.

Most of the fuzzy logic based power quality event classifiers differ in the signal processing techniques applied for feature extraction from the raw signal samples and the fuzzy rule base used for event recognition. For example the FES in [21] uses a Fourier linear combiner and gives 8 rules for power quality event recognition and in [22] wavelet transform is used for building the fuzzy rule base. From these papers it is noted that the fuzzy rule base used by most of the researchers suffer from a lack of robustness as they do not provide the certainty of the rule in classifying a given disturbance event. This paper, therefore, addresses to develop a fuzzy expert system using a data mining principle, where each classification rule of the fuzzy rule base has a certainty factor associated with the rule. The extracted features are fuzzified and accordingly one of the rules is fired to provide the required pattern classification with a certain degree of certainty. Further to improve the accuracy of classification, the parameters of the trapezoidal and Gaussian membership functions are optimized using a fuzzy particle swarm optimization (PSO) technique [23–27]. To bring out the efficacy of this new approach, computer simulations are carried out for the recognition of several synthetic and recorded power quality disturbance signals. Also the well known wavelet based fuzzy classifier is presented in this paper for comparison with the proposed approach for time-series data mining. The paper is organized in five sections: Sections 2 and 3 outline the S-transform based analysis and feature extraction, respectively. Section 4 outlines the development of a fuzzy expert system based on data mining approach. Section 5 describes the adaptive fuzzy particle swarm optimization techniques. Finally simulation results are given in Section 6.

2. Power disturbance signal processing using S-transform

To be able to distinguish and classify the different power quality events occurring in power networks, it is essential to process the original signals by a time-frequency transform technique with a view to extract pertinent information about the signal. Thus the processed signal yields certain unique features for a given power quality event that may be further used for automatic recognition of the event. These disturbance signals are functions of time and hence constitute non-stationary signal patterns that can be described as a time-series. Discretizing these signals yield time series data which is processed by using a time-frequency transform like S-transform.

The multiresolution S-transform originates from two-advanced signal processing tools; the short-time Fourier transforms (STFT) and the wavelet transform. It can be viewed as a frequency dependent STFT or a phase corrected wavelet transform. Due to the frequency dependent window used for analysis of a signal data, the multiresolution S-transform has been proven to perform better than other time-frequency transforms. Furthermore, it provides superior time-frequency localization property computing both amplitude and phase spectrum of discrete data samples. It was shown in [14], that the S-transform would be useful for classifying power signal time series disturbances. Also it is less susceptible to noise than the wavelet transform approach.

The S-transform of a signal $h(t)$ is defined as

$$S(t,f) = \int_{-\infty}^{\infty} h(\tau)w^*(\tau - t, f)\,.e^{-j2\pi f\tau} d\tau \tag{1}$$

where

$$S(t,f) = \frac{|f|}{\alpha\sqrt{2\pi}}.e^{-tf^2/2\,\alpha^2} \tag{2}$$

and * stands for complex-conjugate. The parameter α sets the width of the window for a given frequency. For small α, the time resolution improves and the frequency resolution deteriorates. The reverse happens when α is increased to a larger value. S-transform produces a multiresolution analysis like a bank of filters with constant relative bandwidth. The integration of S-transform over time results in the Fourier spectrum that is

$$H(f) = \int_{-\infty}^{\infty} S(t,f)dt \tag{3}$$

and for the Gaussian window

$$\int_{-\infty}^{\infty} S(t,f)dt = 1 \tag{4}$$

The original signal can be obtained from S-transform as

$$h(t) = \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} S(\tau,f)d\tau \right\} e^{j2f\pi\, t}.\ df \tag{5}$$

Another way to represent S-transform is an amplitude and phase correction of the CWT (continuous wavelet transform) as

$$S(t,f) = \sqrt{\frac{|f|}{2\pi\alpha}} e^{-j2f\pi t} WT(t,f) \tag{6}$$

where the wavelet transform is given by

$$WT(t,f) = \sqrt{\frac{|f|}{\alpha}}.e^{-t^2 f^2/2\alpha^2}.e^{j2\pi ft} \tag{7}$$

Eq. (6) shows that the time-frequency resolution is distributed in the time frequency plane like wavelet transform but a direct link with Fourier transform exists.

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