Applied Soft Computing 9 (2009) 107–117

Contents lists available at ScienceDirect

Applied Soft Computing

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

Non-stationary power signal processing for pattern recognition using HS-transform

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ARTICLE INFO

Article history:
Received 30 May 2007
Received in revised form 21 February 2008
Accepted 11 March 2008
Available online 18 March 2008

Keywords:
Non-stationary power signals
Power quality (PQ)
HS-transform
Genetic algorithm
Fuzzy C-means clustering

ABSTRACT

A new approach to time-frequency transform and pattern recognition of non-stationary power signals is presented in this paper. In the proposed work visual localization, detection and classification of non-stationary power signals are achieved using hyperbolic S-transform known as HS-transform and automatic pattern recognition is carried out using GA based Fuzzy C-means algorithm. Time-frequency analysis and feature extraction from the non-stationary power signals are done by HS-transform. Various non-stationary power signal waveforms are processed through HS-transform with hyperbolic window to generate time-frequency contours for extracting relevant features for pattern classification. The extracted features are clustered using Fuzzy C-means algorithm and finally the algorithm is optimized using genetic algorithm to refine the cluster centers. The average classification accuracy of the disturbances is 93.25% and 95.75% using Fuzzy C-means and genetic based Fuzzy C-means algorithm, respectively.

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1. Introduction

Non-stationary power signal disturbances and power quality (PQ) [1–6] have been a cause for concern for both the utilities and users due to the use of many types of electronic equipments. Harmonics, voltage swell, voltage sag, transients, and momentary interruptions can adversely affect these equipments. These disturbances cause several problems, such as overheating, failure of motors, disoperation of sensitive and protective equipment and inaccurate metering. Voltage swell and sag can occur due to lightning, capacitor switching, motor starting, nearby circuit faults or accidents, and can also lead to power interruptions. Harmonic currents due to nonlinear loads through out the network can also degrade the quality of services to sensitive high-tech customers. To distinguish the non-stationary disturbance signal patterns in the normal sinusoidal signal frequencies, advanced signal processing techniques along with pattern recognition approach play a vital role in classifying the patterns of the non-stationary power signal disturbances. Consequently solutions to electrical network disturbance problems involve continuous monitoring of electrical network voltage and current waveforms at certain customer sites and discretizing these signals into digital data to identify the different disturbance patterns using pattern recognition techniques. When a huge electrical network signal database is used for identifying the similar patterns and its localization in time, it constitutes an important area of non-stationary time series analysis.

To ensure a good power quality, a system must be able to monitor, locate, and classify disturbances by measurement approaches and instruments. These instruments must collect large amounts of measured data such as voltages, currents, and occurrence items. However, they do not automatically classify disturbances and they require offline analysis from the recorded data. Fast Fourier transformation (FFT) has been applied to steady state phenomenon but short-time duration disturbances require short-time Fourier transformations (STFT) to aid the analysis. The choices for size of window affect both the frequency and time resolution when using STFT. On the other hand another transform like the S-transform [7,8] uses an analysis window whose width decreases with frequency providing a frequency-dependent resolution. The S-transform 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 events in a time series like the power quality disturbances.

For the S-transform output with Gaussian window, it is found that disturbances like sag, swell, and momentary interruption are

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doi:10.1016/j.asoc.2008.03.004

not clearly localized in the time domain. To circumvent this problem another variant of the original S-transform [9] known as HS-transform with a pseudo-Gaussian hyperbolic window is used in this paper to provide better time and frequency resolutions at low and high frequencies unlike the S-transform with Gaussian window. Here the hyperbolic window has frequency dependence in its shape in addition to its width and height. The increased asymmetry of the window at low frequencies leads to an increase in the width in the frequency domain, with consequent interference between major noise frequencies. This paper, therefore, uses the HS-transform to process non-stationary power disturbance signals to extract relevant features for power signal pattern recognition.

After the features are extracted from the time-series data using S-transform with a modified Gaussian window, a clustering analysis is used to group the data into clusters and thereby identifying the class of the data. The well-known Fuzzy C-means algorithm [10] is commonly used for data clustering but suffers from trial and error choice of the initial cluster centers and also the noise present in the original time series. In this paper a hybrid Fuzzy C-means and GA (genetic algorithm) [11–16] is used to cluster the features into distinct groups so as to classify the nature of the time series data. GA differs from more traditional optimization techniques in that it involves a search starting from a population of solutions, and not from a single point. Each iteration of a GA involves a competitive selection that weeds out poor solutions using genetic parameters such as crossover and mutation. This generation mechanism provides the ability to overcome local maxima and minima and obtain optimal solutions. In traditional Fuzzy C-means, the program gets stuck in the local minima and, therefore, does not offer robustness in clustering the features.

2. Generalized hyperbolic S-transform (HS-transform)

The S-transform of a time series $u(t)$ is defined as [1]:

$$S(\tau, f) = \int_{-\infty}^{\infty} u(t)w(t-\tau, f)e^{-2i\pi ft}dt \tag{1}$$

For the Gaussian window, we have chosen the window width to be

$$\sigma(f) = \frac{\gamma_{gs}}{|f|} \tag{2}$$

It should be noted that the Gaussian window has a frequency-dependent variance as $(\gamma_{gs}^2/|f|^2)$. The Gaussian window w_{gs} in Eq. (1) is obtained as

$$w_{gs}(\tau-t, f) = \frac{|f|}{\gamma_{gs}\sqrt{2\pi}}\exp\left(-\frac{f^2(\tau-t)^2}{2\gamma_{gs}^2}\right), \quad \gamma_{gs} < 1 \tag{3}$$

where f is the frequency, t and τ are the time variables, and γ_{gs} is a scaling factor that controls the number of oscillations in the window. When γ_{gs} is increased, the window broadens in the time domain and hence frequency resolution is increased in the frequency domain.

Defining a function,

$$P(t, f) = u(t)e^{-i2\pi ft}dt \tag{4}$$

Eq. (1) can be rewritten as a convolution given by

$$S(\tau, f, \sigma) = \int_{-\infty}^{\infty} p(t, f)w_{gs}(t-\tau, f)dt \tag{5}$$

Defining $B(f, \alpha)$ as the Fourier transforms (σ to α) of $S(t, f)$, the convolution becomes a multiplication in the frequency domain:

$$B(f, \alpha) = P(t, f)W(\alpha, f) \tag{6}$$

Explicitly,

$$B(f, \alpha) = U(\alpha+f)e^{-2\pi^2\alpha^2/(f)^2} \tag{7}$$

Eq. (1) can be equivalently written in terms of the Fourier transform (FT) of the signal, taking advantage of the fact that the FT of a Gaussian is a Gaussian and $U(\alpha + f)$ is the Fourier transform of Eq. (4). Thus, an alternative representation for the generalized S-transform with Gaussian window of the relation in Eq. (3) is the inverse Fourier transform $(\alpha - \tau)$ of the relation in Eq. (7) as

$$S(\tau, f) = \int_{-\infty}^{\infty} U(\alpha+f)e^{(-2\pi^2\alpha^2)/(f)^2}e^{2i\pi\alpha\tau}d\alpha \tag{8}$$

In applications, which require simultaneous identification time-frequency signatures of different power quality events, it may be advantageous to use a window having frequency-dependent asymmetry. Thus for transient events at high frequencies a smaller value of γ_{gs} is used where the window is narrowed in the time domain and widened in the frequency domain, with consequent loss of resolution in the frequency direction on the S-transform. As a consequence the identification of the transient event is compromised for $\gamma_{gs} < 1$. Thus, at high frequencies, where the window is wider and frequency resolution is good in any case, a more symmetrical window is used. On the other hand, at low frequencies where a window is wider and frequency resolution is less critical, a more asymmetrical window may be used to prevent the event from appearing too far ahead on the S-transform. Thus a hyperbolic window of the form given below is used:

$$w_{hy} = \frac{2|f|}{\sqrt{2\pi(\alpha_{hy}+\beta_{hy})}}\exp\left\{\frac{-f^2X^2}{2}\right\} \tag{9}$$

where

$$X = \frac{\alpha_{hy}+\beta_{hy}}{2\alpha_{hy}\beta_{hy}}(\tau-t-\xi) + \frac{\alpha_{hy}-\beta_{hy}}{2\alpha_{hy}\beta_{hy}}\sqrt{(\tau-t-\xi)^2+\lambda_{hy}^2} \tag{10}$$

In Eq. (10), X is a hyperbola in $(\tau - t)$, which depends on the backward taper parameter α_{hy} and a forward-taper parameter β_{hy}. In the above expression $0 < \alpha_{hy} < \beta_{hy}$ and ξ is defined as

$$\xi = \frac{\sqrt{(\beta_{hy}-\alpha_{hy})^2\lambda_{hy}^2}}{(4\alpha_{hy}\beta_{hy})^{1/2}} \tag{11}$$

The translation by ξ ensures that the peak w_{hy} occurs at $\tau - t = 0$.

At $f = 0$, w_{hy} is very asymmetrical, but when f increases, the shape of w_{hy} converges towards that of w_{gs}, the symmetrical Gaussian window given in Eq. (2). For different values of α_{hy} and β_{hy} and with $\lambda_{hy}^2 = 1$, Fig. 1 shows the nature of the window as the function of time $\tau - t$. As seen from the figure the change in the shape from an asymmetrical window to a symmetrical one occurs more rapidly with increasing f. The discrete version of the hyperbolic S-transform of the and power quality signal samples is calculated as

$$S[n, j] = \sum_{m=0}^{N-1} H[m+n]G(m, n)\exp(i2\pi mj) \tag{12}$$

where N is the total number of samples, and $G(m, n)$ denotes the Fourier transform of the hyperbolic window and is given by

$$G(m,n) = \frac{2|f|}{\sqrt{2\pi(\alpha_{hy}+\beta_{hy})}}\exp\left(\frac{-f^2X^2}{2n^2}\right) \tag{13}$$

and

$$X = \frac{(\alpha_{hy}+\beta_{hy})}{2\alpha_{hy}\beta_{hy}}t + \frac{\beta_{hy}-\alpha_{hy}}{2\alpha_{hy}\beta_{hy}}\left(\sqrt{t^2+\lambda_{hy}}\right) \tag{14}$$

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