Available online at www.elixirpublishers.com (Elixir International Journal)

Electrical Engineering

Elixir Elec. Engg. 53 (2012) 11815-11818

ISSN: 2229-712X

Analysis of Non-Stationary Power Quality Signals

M. Venkata Subbarao, N.Sayedu Khasim and Jagadeesh Thati

Department of Electronics and Communications, Tirumala Engineering College (AP.), India.

ARTICLE INFO

Article history:

Received: 9 October 2012;
Received in revised form:
20 November 2012;
Accepted: 3 December 2012;

Keywords

Power Quality (PQ) signals,
Time-Frequency Analysis,
Wavelet Transform (WT),
S-Transform (ST).

ABSTRACT

Spectral analysis using the Fourier Transform is a powerful technique for stationary time series where the characteristics of the signal do not change with time. For non-stationary time series, the spectral content changes with time and hence time-averaged amplitude spectrum found by using Fourier Transform is inadequate to track the changes in the signal magnitude, frequency or phase. This paper presents a new time-frequency signal analysis method, called Modified S-Transform (MST) with modified Gaussian window, for visual localization, detection of various non-stationary power signals.

1. Introduction

Time–frequency analysis has been successfully used in dealing with rapidly varying transient signals, such as guided-wave signals and damping vibration signals [1]. For Time–Frequency Representations (TFRs), the Short-Time Fourier Transform (STFT), the Wigner-Ville distribution (WVD) and the Wavelet Transform (WT) are commonly used. STFT and WVD have certain advantages over the WT, but they also have some critical limitations in comparison with the WT. The fixed time–frequency window of STFT can lead to undesirable time and frequency resolutions. In spite of its excellent time–frequency resolution, using WVD, it is often difficult to analyze a signal with composite-frequency components because of the appearance of interference terms.

In the case of the WT, however, the window size changes adaptively to the frequency component because of its constant bandwidth-to-frequency ratio property [2–4]. In other words, this analysis uses a shorter time window for higher frequency components and a longer window for lower- frequency components. In fact, WT is only an extension of STFT in time domain with the constant bandwidth-to- frequency ratio. Unfortunately, even if under the same bandwidth-to-frequency ratio, the WT may have different TFR features [5]. Since the wavelet window function must satisfy the strict admissible condition, the WT often creates two problems.

The first one is the center of time–frequency window, which usually is not the observing center, and the other is the fact that most of wavelet functions are not symmetric. Therefore, the time–frequency window of the WT will lose the easy operation in application and theory analysis, especially in the frequency domain. Moreover, it is often not convenient in application that the WT uses the scale instead of the observing frequency. Comparing with STFT, the WT can extract more accurately the instantaneous frequency information of signals, but the most important issue in the time–frequency analysis is how to achieve the best time–frequency energy localization for given signals. For instance, this localization is often employed to locate the arrival time and estimate the dispersed frequency of guided-wave signal.

Nevertheless, the characteristic of the mother wavelet function significantly affect the performance of the time-frequency analysis of the Wavelet Transform (WT). For example, although the Gabor wavelet, which is one of the most widely used analytic wavelets, has the best time–frequency resolution, i.e. the smallest Heisenberg box, the center frequency and the time supporting width of the mother Gabor wavelet affect its time–frequency decomposition characteristics. This means that, depending on the signals to be analyzed, different Gabor wavelet shapes must be used. Since the characteristics of signals are unknown in general, the determination of the optimal shape is usually difficult [6].

Recently Power Quality (PQ) and related power supply issues have become quite a serious problem both for the end user as well as the utilities. The PQ issues and related phenomena can be attributed to the use of solid-state switching devices, unbalanced and non-linear loads, industrial grade rectifiers and inverters, computer and data processing equipments etc. These devices introduce distortions in the phase, frequency and amplitude of the power system signal thereby deteriorating PQ. Hence analysis of PQ related issues are indispensable and this has been the focus of the researchers in the past decade.

Current advances in signal analysis have led to the development of a new method for non-stationary signal analysis called Modified S-Transform (MST).

The MST is an extension of the Short Time Fourier Transform in time domain and it allows a signal to be analyzed in terms of both time and frequency. The MST is an extension of the short time Fourier transform in time domain and it allows a signal to be analyzed in terms of both time and frequency simultaneously.

2. THE MODIFIED S-TRANSFORM

The ST of a time series $x(t)$ is defined as

$$s(t,f)=\int_{-\infty}^{\infty} x(\tau)w(t-\tau,f)e^{-2i\pi f\tau}d\tau$$
$$=\int_{-\infty}^{\infty} x(\tau)\frac{1}{\sigma(f)\sqrt{2\pi}}e^{\frac{-(t-\tau)^2}{2\sigma(f)^2}}e^{-2i\pi f\tau}d\tau \qquad (1)$$

Tele:
E-mail addresses: jagadeeshthati@gmail.com

The standard deviation $\sigma(f)$ of the window w of the standard S-transform in equation (1) is

$$\sigma(f)=1/|f| \quad (2)$$

For the modified Gaussian window, we have chosen the standard deviation $\sigma(f)$ to be

$$\sigma(f)=k/(a+b/\sqrt{f}) \quad (3)$$

Where a,b are positive constants, f is signal fundamental frequency and $k\leq\sqrt{a^2+b^2}$. In equation (1), the usually chosen window w is the Gaussian one. Thus, the spread of the original Gaussian function is being varied with frequency to generate the new modified Gaussian window as

$$w(t,f)=\frac{a+b\sqrt{|f|}}{k\sqrt{2\pi}}e^{-\frac{(a+b\sqrt{f})^2t^2}{2k^2}}, k>0 \quad (4)$$

In which *f* is the frequency, *t* and τ the time variables and *k, b* are scaling factors that control the number of oscillations in the window; a is a constant. When *k* is increased, the window broadens in the time domain and hence frequency resolution is increased in the frequency domain. Again by setting *b=0* and *k=1* we can obtain the Short -Time Fourier Transform explicitly. Thus, an alternative representation for the Generalized S- transform with modified Gaussian window is

$$S(\tau,f)=\int_{-\infty}^{\infty}X(\alpha+f)e^{(-2\pi^2\alpha^2K^2)/(a+b\sqrt{|f|})^2}e^{2i\pi\alpha\tau}d\alpha \quad (5)$$

The discrete version of the S-Transform of a signal is obtained as

$$S[j,n]=\sum_{m=0}^{N-1}X[m+n]e^{(-2\pi^2m^2K^2/(a+b\sqrt{|f|}^2)}e^{i\frac{2\pi mj}{N}} \quad (6)$$

Where X[m+n] is obtained by shifting the discrete Fourier Transform (DFT) of $x(k)$ by n, $X[m]$ being given

$$X[m]=\frac{1}{N}\sum_{k=0}^{N-1}x[k]e^{-j\frac{2\pi mk}{N}} \quad (7)$$

Further S Transform of signal $x(t)$ and noise $\eta(t)$ is

$$S(x(t)+\eta(t))=S(x(t))+S(\eta(t)) \quad (8)$$

From equation (8) it can be seen that the noise can be removed from the S-Transform output by a simple thresholding technique.

3. RESULTS AND DISCUSSION

In our study we have discussed different types of power signal waveforms such as voltage flicker, transient, momentary interruption, some simultaneous cases, and noisy cases. The time-frequency contours of these disturbances and their corresponding change in magnitude vs. time are analyzed with MATLAB software. The chosen sampling rate is 3.84 kHz. The MST outputs show the plots of the normalized frequency contours of a given magnitude in the time-frequency co-ordinate system.

Fig. 1-5, and Fig. 7, shows the time-frequency contours of some typical PQ disturbances with MST, and these contours clearly the nature of disturbances in the presence of noise. For example, Fig. 1(a) actual signal showing nearly four-cycles voltage Interruption. In Fig. 1(b) the normalized time-frequency contour from MST is shown. Fig. 1(c) gives the magnitude-time spectrum obtained by searching rows of MST matrix.

Fig. 2, Fig. 3 (a)-(c), show similar plots as in Fig. 1 obtained from MST analysis. The time-frequency contours of the MST output shows a decrease or increase in magnitude for voltage flicker and for voltage transient which provide a better visual classification strategy in comparison to the wavelet transform.

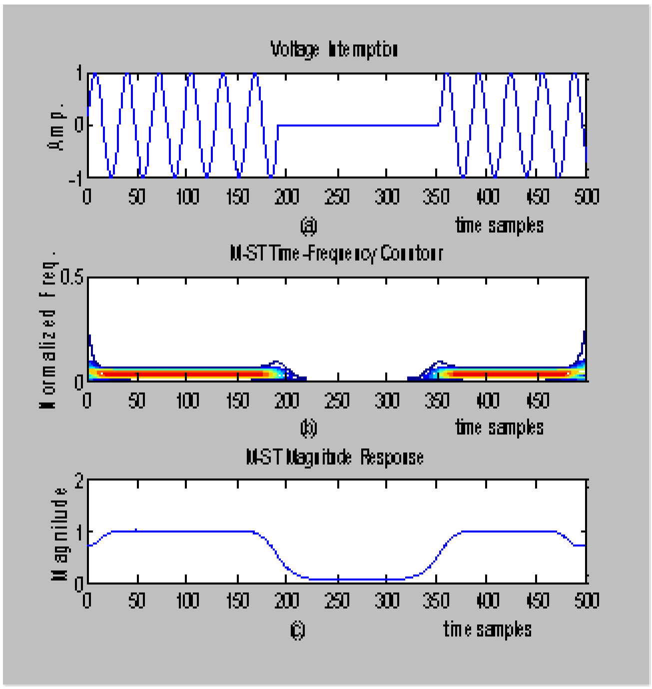

Fig.1 (a) Momentary Interruption (b) Modified ST time-frequency contour (c) Modified ST magnitude response

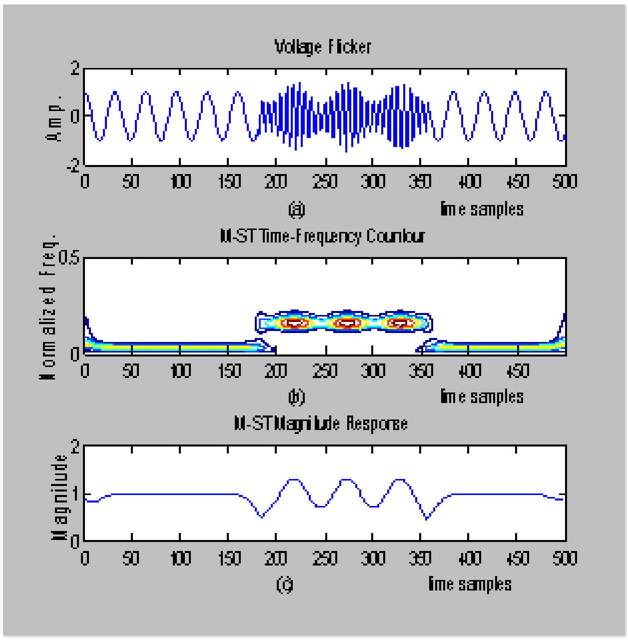

Fig. 2 (a) Voltage Flicker (b) Modified ST time-frequency contour (c) Modified ST magnitude response.

Fig. 4 represents simultaneous disturbances occurred in the voltage signal. Fig. 4(a)-(c), shows similar plots as in Fig. 1-Fig. 3 obtained from MST analysis. The time-frequency contours of the MST output shows increase in magnitude for voltage swell and zero magnitude for voltage interruption which provides a better detection, localization and visual classification.

Fig. 5(a) represents a simulated Gaussian signal having three different frequency Gaussian signals centered at different time intervals. Fig. 5(b), represent time frequency contour of simulated Gaussian signal, and here we can observe that three different frequency Gaussian signals were localized to different time intervals. Fig. 6 represents scalogram for the simulated Gaussian signal that was shown in Fig. 5(a). Here the scalogram represents percentage of energy for each Modified or modified ST coefficient.

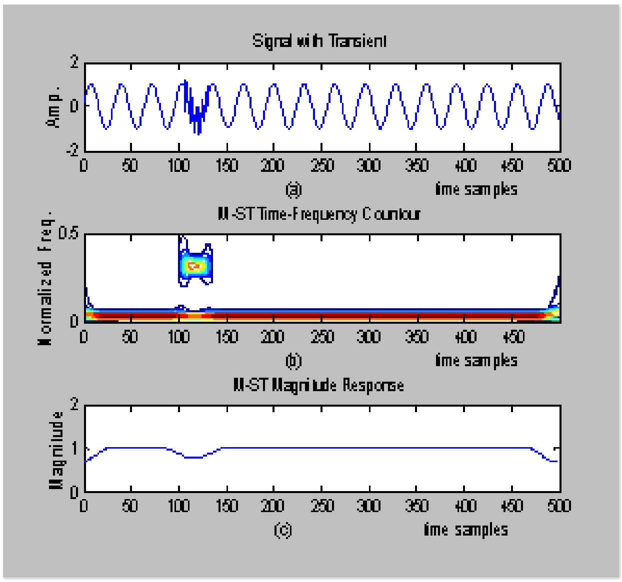

Fig. 3 (a) Voltage Transient (b) Modified ST time-frequency contour (c) Modified ST magnitude response

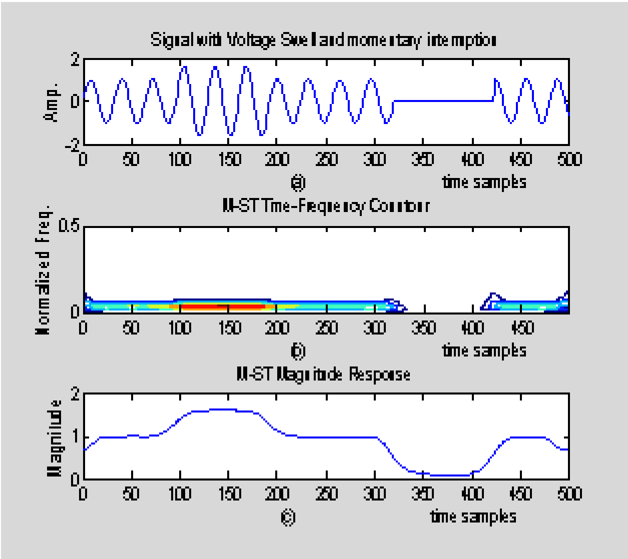

Fig. 4 (a) Simultaneous Disturbances (b) Modified ST time-frequency contour (c) Modified ST magnitude response

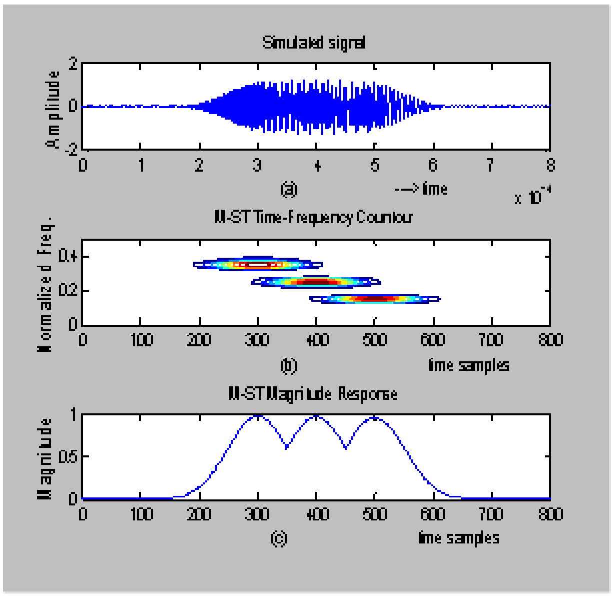

Fig. 5 (a) Simulated Gaussian signal (b) Modified ST time-frequency contour (c) Modified ST magnitude response.

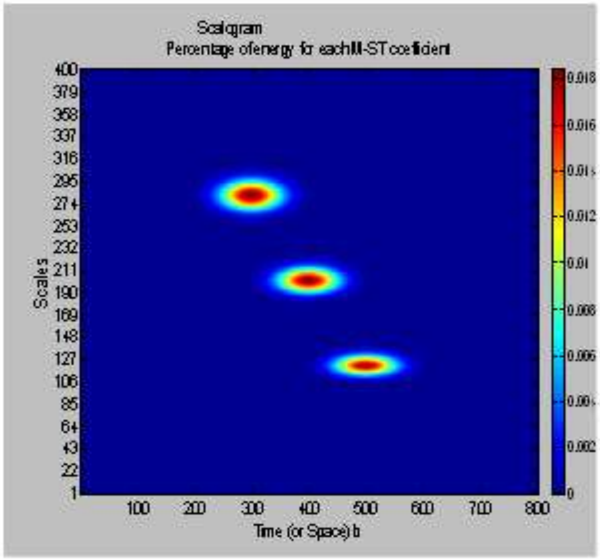

Fig. 6 Scalogram for the simulated Gaussian signals.

Fig. 7(a) represents a simulated Gaussian signal with 25 dB noise. Fig. 7(b), represent time frequency contour of simulated Gaussian signal with noise, and here we can observe that there is no effect on the time-frequency contour. Fig. 8 represents scalogram for the simulated Gaussian signal with 25 dB noise that was shown in Fig. 7(a).

From this analysis we can say that MST is more powerful method for time-frequency analysis of non-stationary signals when compared to existing techniques.

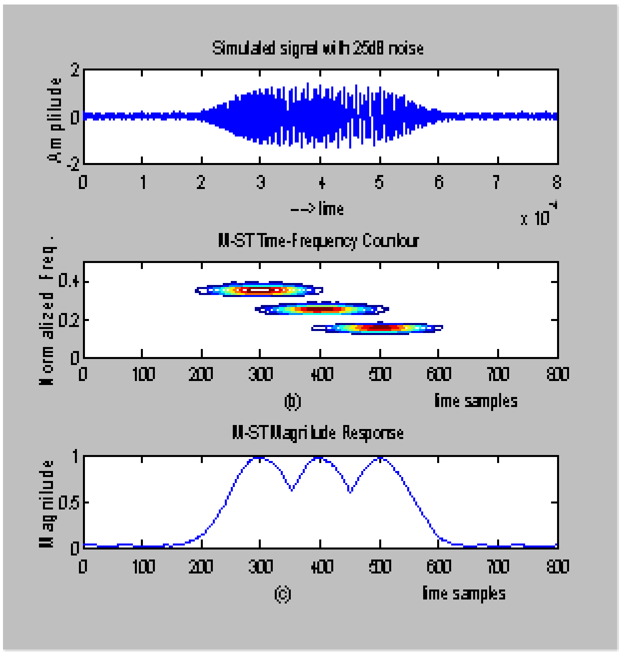

Fig. 7 (a) Simulated Gaussian signal with 25dB noise (b) Modified ST time-frequency contour (c) Modified ST magnitude response

4. CONCLUSION

This paper has proposed a new approach for detection and localization of power quality disturbances in a power distribution system. The S-Transform with modified Gaussian window is used in this paper as a powerful analysis tool for detection, localization and visual classification of non-stationary power signal waveforms**.** The Modified S-Transform (MST) with modified Gaussian window gives better localization even in the presence of noise when compared with generalized S-Transform. In future this method can be widely applied to image processing, Radar signal detection and classification and seismic signal processing.

Automatic classification can be done by extracting feature vector from the MST frequency contour and finally passing those pertinent feature vectors through an intelligent classifier for pattern classification.

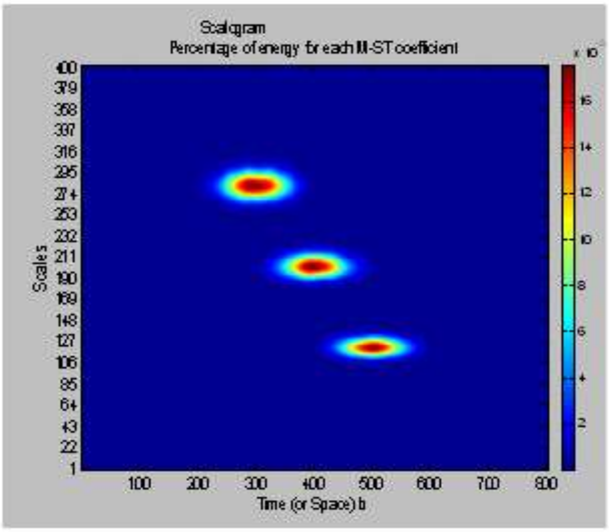

Fig. 8 Scalogram for the simulated Gaussian signal with 25dB noise

REFERENCES

1. S.A. Neild, P.D. McFadden, M.S. Williams, A review of time–frequency methods for structural vibration analysis, Engineering Structures 25 (2003) 713–728.
2. S. Qian, Introduction to time–frequency and wavelet transforms, Prentice-Hall PTR, Upper Saddle River, NJ, 2002.
3. S. Mallat, A Wavelet tour of Signal Processing, Academic Press, New York, 1998.
4. Zhonghong Yan, Ayaho Miyamoto,Zhongwei Jiang, Xinglong Liu, An overall theoretical description of frequency slice wavelet transform, Mechanical ystems and Signal Processing 24 (5) (2010) 491–507.
5. J.-C. Hong, Y.Y. Kim, The determination of the optimal Gabor wavelet shape for the best time–frequency localization using the entropy concept, Experimental Mechanics 44 (2004) 387–395.
6. Ingrid Daubechies, Ten Lecture on Wavelets, CBMS-NSF Regional Conference Series in Applied Mathematics, vol. 61, SIAM Philadelphia, 1992.