Complex Cepstrum based Analysis of Power Quality Events and its Comparison with Time-Frequency Analysis Methods

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***Abstract*: Monitoring of events in the power system provides a great deal of insight into the behavior of the system. Power quality of electric power system has become an increasing concern for electric utilities and their customers over the last decade. The goal of monitoring non-stationary signal is to quantify the dynamic nature of these signals and to extract the important features that support the integrated monitoring system that can be used in maintenance scheduling and system operation. This paper documents an alternate method called cepstrum defined as Inverse Fourier Transform of a logarithmic spectrum has been used to analyze different power system events. Its performance has been compared with other time-frequency analysis methods like spectrogram, wavelet and scalogram. Cepstrum can detect the change in amplitude, frequency and phase accurately.**

***Keywords*: complex cepstrum, spectrogram, wavelet transform, scalogram, power system events**

I. INTRODUCTION

Power quality (PQ) has been a research area of exponentially increasing interest particularly in the past decade. The proper diagnosis of PQ problems requires a high level of engineering expertise. Adding to the difficulty of PQ diagnosis, is that the required expert knowledge is not in any one area but rather in many areas of electric power, e.g., electric drives, sensors, rotating machines, transformers, power electronics, power supplies, capacitor switching, protection, power system faults, harmonics, signal analysis, measuring instruments, and general power systems operation. A PQ problem could be defined as being "any power problem manifested in voltage, current, or frequency deviations that result in failure or maloperation of customer equipment". PQ involves research in several areas that are related to the main aspects of the quality of electric power. These areas may be summarized as basic concepts and definitions, modeling and analysis, measurement and instrumentation, feature extraction techniques, sources of PQ problems, effects of PQ deterioration, problem analysis and diagnosis, solutions to and mitigation of PQ problems, and educational issues related to power quality. The artificial intelligence techniques such as fuzzy logic, expert system, neural network, genetic algorithm and advanced mathematical techniques like wavelets, Slantlet, DCT have been used for the analysis of power quality [1] – [8].

A new method of analyzing power quality has been discussed in this paper which has found its application in many other fields discussed below**.** The cepstrum can be viewed as information about the rate of change in the different spectrum bands. It was originally invented for characterizing the seismic echoes resulting from earthquakes and bomb explosions. It has also been used to determine the fundamental frequency of human speech and to analyze radar signal returns. It is used for voice identification, pitch detection, analysis of filter stability, etc [9]-[23]. The independent variable of a cepstral graph is called quefrency. The quefrency is a measure of time, though not in the sense of a signal in the time domain. The most employed type of cepstrum is the concept of complex cepstrum (CC), which is capable of converting two convolved signals in one space as added pairs in another one. Cepstrum analysis is an effective method for fault detection of gearbox and bearings in electrical machines. Section II explains about cepstrum and its types, section III discusses on spectrogram, section IV on wavelet transform and scalogram in section V and the results of analyzing the different power system events using the above methods are presented in section VI. The conclusions are given in section VII.

II. CEPSTRUM

A **cepstrum** is the result of taking the Fourier Transform of the log spectrum. It was derived by reversing the first four letters of spectrum. The types of cepstrum are **complex cepstrum, real cepstrum or power cepstrum and phase cepstrum.** There are many ways to calculate the cepstrum. Some of them need a phase-unwarpping algorithm but others do not. Operations on cepstra are labeled quefrency analysis, liftering or cepstral analysis [18]-[20].

A. Complex Cepstrum

The complex cepstrum of a signal h(t), given by (1) and shown schematically in Fig. 1 is written $\hat{h}(t)$, and is defined as Inverse Fourier Transform of the (complex algorithm of the signal) natural algorithm of its Fourier Transform.

$$\hat{h}(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \ln(H(\omega))e^{j\omega t}d\omega \qquad (1)$$

The complex cepstrum is a real function because it is the transform of a complex function $\ln(H(\omega)) = \ln|H(\omega)| + j\phi_h$. Since the log magnitude is an even function of frequency and phase is an odd function of frequency, their inverse transforms are real function of time, the complex cepstrum can be divided into an even part and an odd part as in (2).

$$\hat{h}(t) = \hat{h}_e(t) + \hat{h}_o(t) \qquad (2)$$

$\hat{h}_e(t)$ is the even part of the complex cepstrum

$\hat{h}_o(t)$ is the odd part of the complex cepstrum

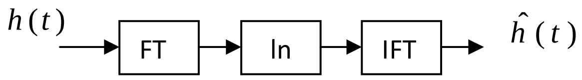


Fig.1 Steps to compute Complex Cepstrum

B. Power Cepstrum

The power cepstrum $C_h(t)$ of signal *h(t)* is given by (3) and schematically shown in Fig. 2 and is defined as inverse Fourier transform of the natural logarithm of its power spectrum (magnitude of its Fourier transform).

$$C_h(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \ln|H(\omega)|e^{j\omega t}d\omega \qquad (3)$$

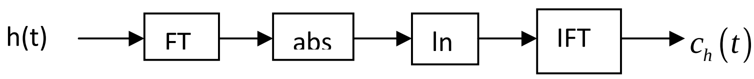


Fig.2 Steps to compute Power Cepstrum

The power cepstrum is the even part of the complex cepstrum, as in (4)

$$C_h(t) = \hat{h}_e(t) \qquad (4)$$

C. Phase Cepstrum

The phase cepstrum $C_{\phi h}(t)$ of signal *h(t)* is given by (5) and is defined as the inverse Fourier transform of the phase of its Fourier transform

$$C_{\phi h}(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \arg(H(\omega))e^{j\omega t}d\omega \qquad (5)$$

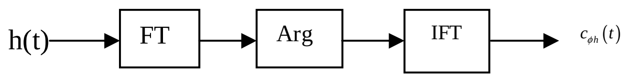


Fig.3 Steps to compute Phase Cepstrum

The phase cepstrum is the odd part of complex cepstrumas in (6).

$$C_{\phi h}(t) = \hat{h}_o(t) \qquad (6)$$

Complex cepstrum has been used to analyze a sawtooth signal shown in Fig.4(a), its logarithmic absolute Fourier Transform has been shown in Fig.4(b) in which the highest peak occur at 50Hz and 100Hz with side bands, its difference is 50Hz which is fundamental frequency, its inverse is 0.02s in time base and its cepstrum is shown in Fig.4(c). The indications in the cepstrum appears at the multiples of 0.02s represents the presence of sidebands at that time instance and it comes from leftmost for signals with duty cycle less than or equal to 0.5 and for signals with duty cycle greater than 0.5 it appears at the rightmost has shown in Fig.(5).

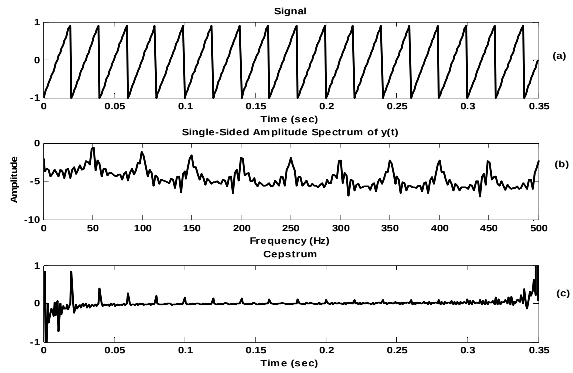


Fig.4 (a) Signal (b) log magnitude specturm (c) cepstrum for a sawtooth

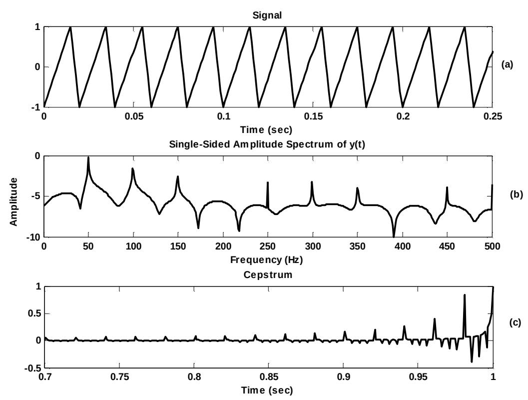


Fig.5 (a) Signal (b) log magnitude specturm (c) cepstrum of a sawtooth signal with 0.75 duty cycle

III. SPECTROGRAM

The Time-Frequency analysis namely spectrogram has been used for the signal analysis. The spectrogram of the signal represents the signal's energy at time frame t and frequency f. The time localization can be obtained by suitably pre-windowing the signal, as the Discrete Fourier Transform (spectrum) does not show the time localization of frequency components explicitly. The spectrogram is a time-frequency distribution based on the Fourier Transform of the product of a sliding window $h(t)$ with the signal. It is given by the following expression for a signal $x(t)$ is

$$S_x(t,f) = \left| \int_{-\infty}^{+\infty} x(\tau) h^*(\tau - t) e^{-j2\pi f \tau} d\tau \right|^2 \qquad (7)$$

where $t' = \tau$. The length of the sliding window $h^*(t)$ determines time and frequency resolution, i.e., a good frequency resolution needs a long observation window and therefore leads to a bad localization in time and vice versa. The window length has to be chosen based on the prior knowledge of the signal.

IV. DISCRETE WAVELET TRANSFORM

The principle of wavelet transform lies in the hierarchical decomposition of an input signal into a series of successively lower resolution signals, providing an effective way of looking at a signal at various scales and analyzing it with various resolutions. Wavelet can be shown with a very desirable frequency and time characteristics, allowing the visualization with the short window at high frequencies and long window at low frequencies. By this way, the characteristics of nonstationary signal can be better monitored [2].

The DWT of a signal *x* is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response *g* resulting in a convolution of the two:

$$y[n] = \sum_{k=-\infty}^{\infty} x[k] g[n-k] \qquad (8)$$

The signal is also decomposed simultaneously using a high-pass filter *h*. The output gives the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass) as shown in Fig. 6. It is important that the two filters are related to each other and they are known as a quadrature mirror filter.

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k] g[2n-k]$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k] h[2n-k] \qquad (9)$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so that the frequency resolution has been doubled.

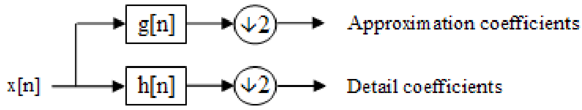


Fig.6 Block diagram of filter analysis

Computing a complete convolution $x * g$ with subsequent downsampling would take more computation time. The Lifting scheme is an optimization where these two computations are interleaved.

A. Cascading and Filter banks

This decomposition is repeated to further increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters and then down-sampled. This is represented as a binary tree with nodes representing a sub-space with a different time-frequency localization. The tree is known as a filter bank.

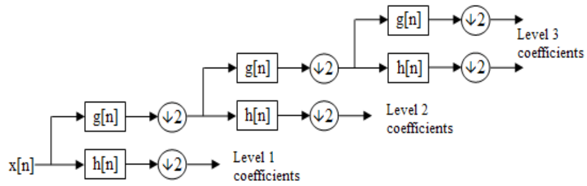


Fig.7 A 3 level filter bank

At each level in the Fig. 7 the signal is decomposed into low and high frequencies. Due to the decomposition process the input signal must be a multiple of 2^n where n is the number of levels and f_n is half the sampling frequency.

For example a signal with 32 samples, frequency range 0 to f_n and 3 levels of decomposition, 4 output scales are produced:

Level	**Frequencies**	**Samples**
3	0 to $f_n / 8$	4
	$f_n / 8$ to $f_n / 4$	4
2	$f_n / 4$ to $f_n / 2$	8
1	$f_n / 2$ to f_n	16

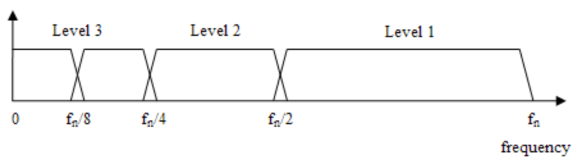


Fig. 8 Frequency domain representation of the DWT

V. SCALOGRAM

The formula for the continuous wavelet transform is

$$C(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} w\left(\frac{t-b}{a}\right) x(t) dt \qquad (10)$$

The function *w(t)* is called the mother wavelet or small wave, a and b are scaling and shifting factors and *x(t)* is the input signal. The continuous wavelet transform (CWT) is the inner product or cross correlation of the signal *x(t)* with scaled and time shifted wavelet $w((t-b))/\sqrt{a}$. This cross correlation is a measure of the similarity between signal and the scaled and shifted wavelet. Magnitude of continuous wavelet transform is called the scalogram. Scalogram can be represented as the two dimensional representation of time in the horizontal axis, scale on the vertical axis and amplitude given by a gray-scale color. The conversion between scale a, to frequency can be made by using formula $5/2\pi a$.

VI. TEST RESULTS

The proposed cepstrum technique is applied to many issues such as: sag, swell, harmonics, interrupt, oscillatory transient and flicker. All the data are generated using the MATLAB code at a sampling frequency of 1kHz. To demonstrate the efficacy of the technique some test cases are presented below. For all simulation study a pure sinusoidal signal of 50Hz and 1p.u amplitude is considered. To compare the performance of the new approach with spectrogram, wavelet and scalogram, the same signal for all the 3 cases has been considered. This clearly demonstrates the better detection capability of the new technique [6].

A. Signal with Voltage swell

When the voltage signal increases by 10%-90% it is known as voltage swell. During a single-line-to-ground fault or when heavy motor loads are switched off, a brief increase of the rated system voltage may take place on the unfaulted phases of a three phase system. This scenario is often seen as voltage swell, whose magnitude is related to the system grounding. Swell may stress the delicate equipment components to premature failure.

A 20% voltage swell begins at t=0.1s and ends at 0.2s. the test waveform sampled at the rate of 1kHz with frequency 50Hz and amplitude 1p.u, is shown in Fig.9 (a), its cepstrum in Fig.9 (b), approximation and detailed coefficients of one level decomposition using haar wavelets is shown in Fig.9 (c) and Fig.9 (d) and its scalogram is shown in Fig 9 (e). cepstrum with disturbance, wavelets and scalogram detects accurately the swell in the signal from 0.1s to 0.2s.

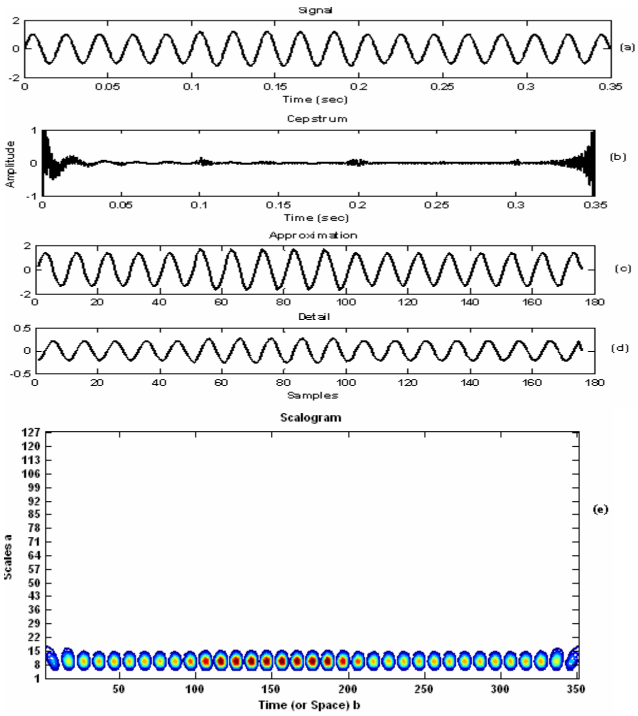


Fig.9 (a)Signal (b)Cepstrum (c)Approximaion (d) Detail (e) Scalogram of a signal with swell

B. Signal with voltage sag

Voltage sags are 10% to 90% reductions in the rated voltage, mainly caused by the short circuits and starting of large motors. Switching operation associated with temporary disconnection of supply, flow of heavy current associated with the starting of large motor load or the flow of fault currents. The effect of voltage sag on equipment depends on both the magnitude and its duration. Adjustable-speed drives, process-control equipment, and computers are considered to the most affected due to sag, because of their sensitivity. The voltage sag lasts for 0.5 cycles to 1min. when the voltage drops 30% or more, the system status is considered to be severe. Voltage sag is not as damaging as interrupt, until it exist for a longer duration in industry.

A 20% voltage sag begins at t=0.1s and ends at 0.2s. the test waveform sampled at the rate of 1kHz with frequency 50Hz and amplitude 1p.u, is shown in Fig 10 (a), its cepstrum in Fig.10 (b), approximation and detailed coefficients of one level decomposition using haar wavelets is shown in Fig.10 (c) and Fig.10 (d) and its scalogram is shown in Fig.10 (e). cepstrum, wavelets, scalogram detects accurately the sag in the signal from 0.1s to 0.2s.

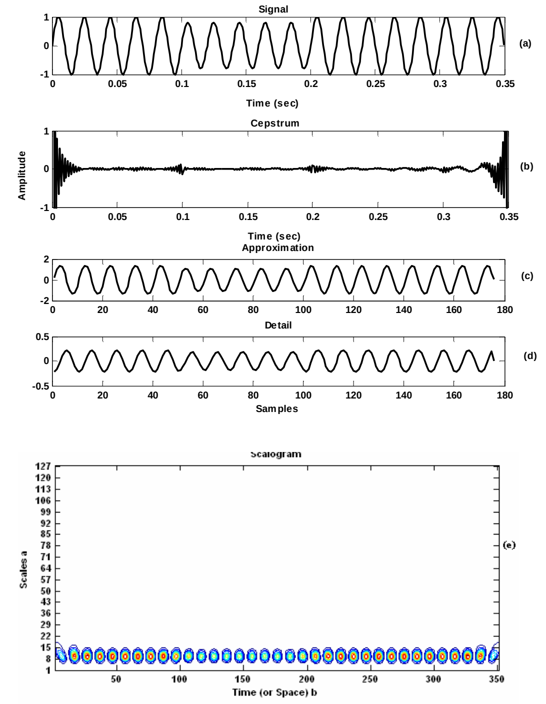
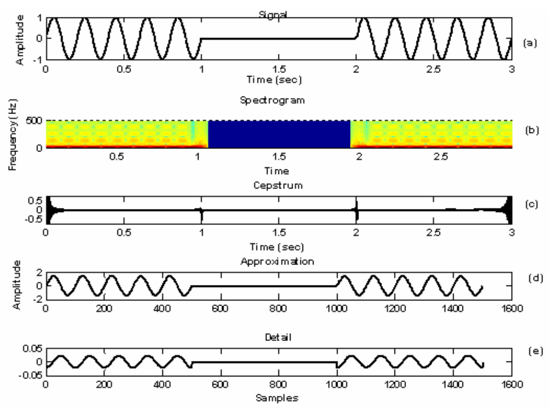


Fig.10 (a)Signal (b)Cepstrum (c) approximation (d)Detail (e)Scalogram of a signal with sag

C. Signal with voltage Interrupt

Interruption is loss of power. A momentary interruption is defined as the drop of 90% to 100% of the rated system voltage lasting for 0.5 cycles to 5min. Their measurement is associated with the operation of reclosing or automatic throw over devices. Supply interruption for few cycles will greatly influence the performance of glass and computer industries.

An interruption in voltage begins at t=1s and ends at 2s. the test waveform sampled at the rate of 1000Hz with frequency 50Hz and amplitude 1p.u, is shown in Fig.11 (a), its cepstrum in Fig.11 (b), approximation and detailed coefficients of one level decomposition using haar wavelets is shown in Fig.11 (c) and Fig.11 (d) and its scalogram is shown in Fig.11 (e). cepstrum also detects the interruption, but with some disturbance. Wavelets, scalogram detects accurately the interruption in the signal from 0.1s to 0.2s.



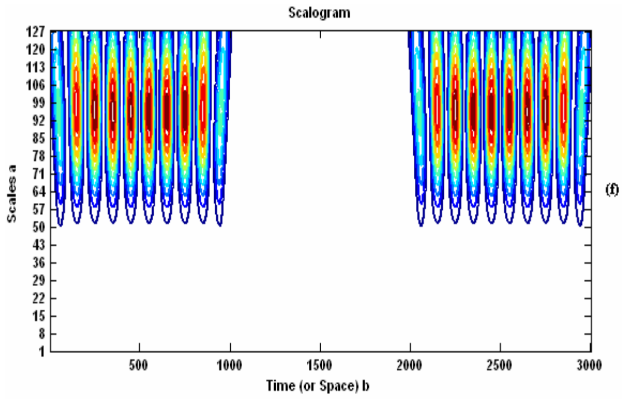
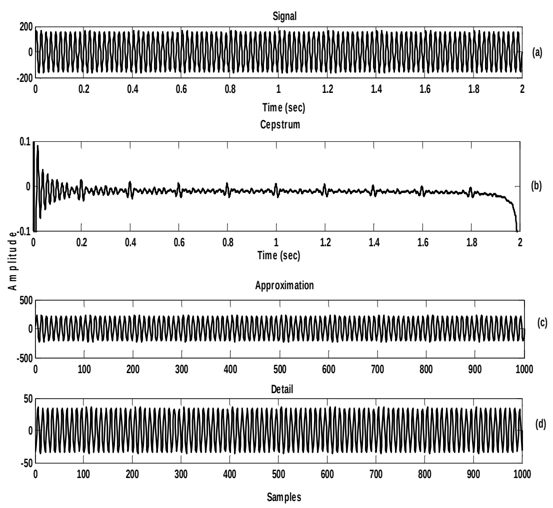


Fig.11 (a) Signal (b) Spectrogram (c)Cepstrum (d) approximation (e)detail (f)Scalogram of a signal with interruption.

D. Signal with voltage flicker

Large nonlinear loads, e.g., arc furnaces and welders result in voltage modulation, where the fundamental power frequency (50 Hz) represents the carrier signal. These low-frequency (0.5-30Hz) modulations are referred as voltage flicker. Voltage flicker can cause objectionable light fluctuations and disruption of sensitive electronic equipments. Cyclic and acylic loads with temporal variation or sudden starting of large induction motors can cause voltage flicker. Measurement, monitoring, prediction and compensation of voltage flicker is of concern for power quality enhancement.

A voltage signal (110V, 50Hz) is modulated by low frequency components with voltages (0.5V, 1Hz), (1V, 5Hz), (2V, 10Hz), (1.5V, 15Hz) and (1V, 20Hz). A signal with flicker is shown in Fig. 12 (a), its cepstrum in Fig. 12 (b), approximation and detailed coefficients of one level decomposition using haar wavelets is shown in Fig. 12 (c) and Fig. 12 (d) and its scalogram in Fig. 12 (e). As the flicker modulates the line voltage, the cepstrum detects the flicker as shown in Fig. 12 (b). Wavelet's detailed coefficients track flicker, but not prominent as in cepstrum. Scalogram does not detect the flicker.



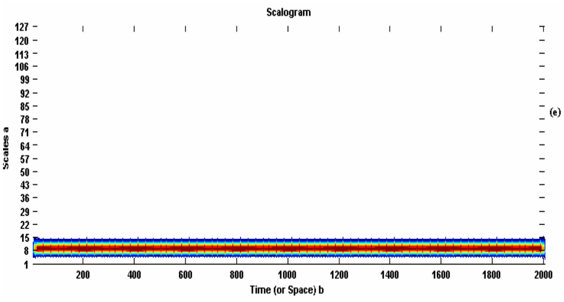


Fig.12 (a)Signal (b) Cepstrum (c)Approximation (d)Detail (e)Scalogram of a flicker.

E. Signal with transients

If the disturbance duration is shorter than sags and swells, they can be categorized as transients. When transients exhibit impulsive characteristics, they are called impulsive transient which are often caused by the lightning or the load switching. When transients display oscillatory characteristics, they are called oscillatory transient which often result from the capacitor switching. Such cases may happen when utility capacitor banks are customarily switched into service early in the morning in anticipation of a higher power demand. In this test, we concentrate on investigating the oscillatory transient, however, the method can be also applied to detect impulsive transients.

A sine signal with frequency 50Hz, amplitude 1p.u with oscillatory transients, sampled at 1kHz as shown in Fig. 13(a), cepstrum in Fig. 13(b), approximation and detailed coefficients of one level decomposition using haar wavelets is shown in Fig. 13(c) and Fig. 13(d) and its scalogram is shown in Fig. 13(e). cepstrum, wavelets detects accurately the change in disturbance in signal at 0.05s, but in the scalogram the disturbance is not detected.

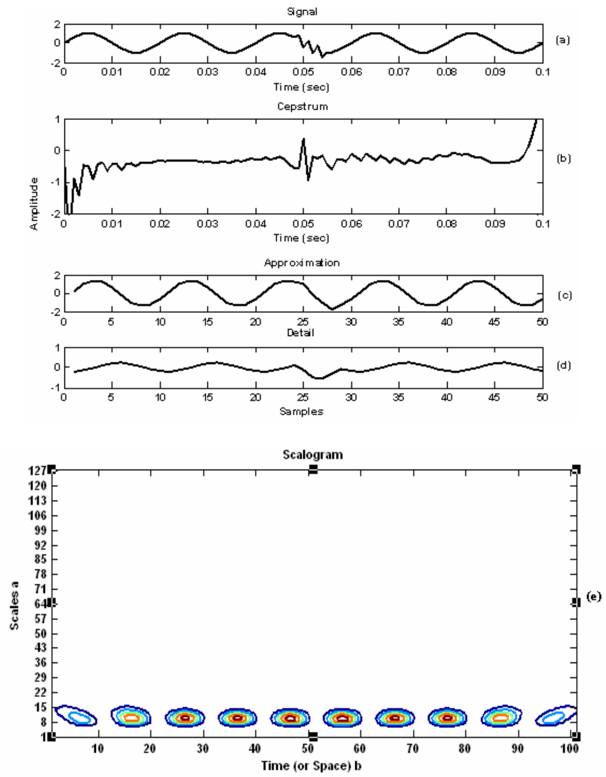
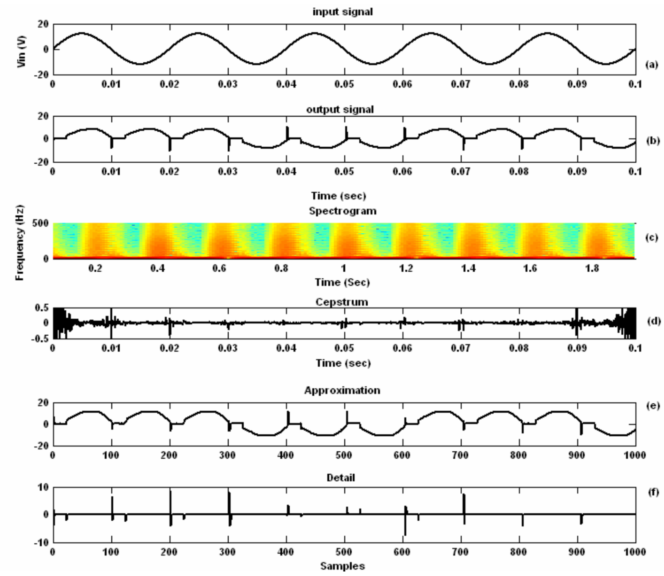


Fig.13 (a)Signal (b)cepstrum (c)Approximation (d)Detail (e) Scalogram for a signal with disturbance.

F. Matrix converter

Cycloconverters are used in high power applications such as variable frequency speed control for ac machines, constant frequency power supplies, controllable reactive power supply for an AC system and induction heating systems. Matrix converter [24-26] is a forced commutated converter that uses an array of controlled bi-directional switches as the main power elements to create a variable output voltage system with unrestricted frequency. It does not have any DC-link unit and does not need any large energy storage elements. In the conventional single phase matrix-converter the AC output voltage cannot increase the input voltage and both bi-directional switches of any phase leg can never be turned on at the same time. The single phase matrix converter that can convert the frequency from 50 to 50 Hz and 50 to 50/3Hz with resistive and inductive load as 100Ω and 20mH has been implemented in hardware using PIC16F877A. The output from the matrix converter has been analyzed using spectrogram, cepstrum, wavelets and scalogram as shown in the Fig.14 and Fig.15. Spike occurs in the output signal due to the inductive load. cepstrum, wavelets detects the spikes in the outputs signal of the matrix converter accurately, but spectrogram with less time resolution. Table II discusses on different power system events detection capabilities of various methods.



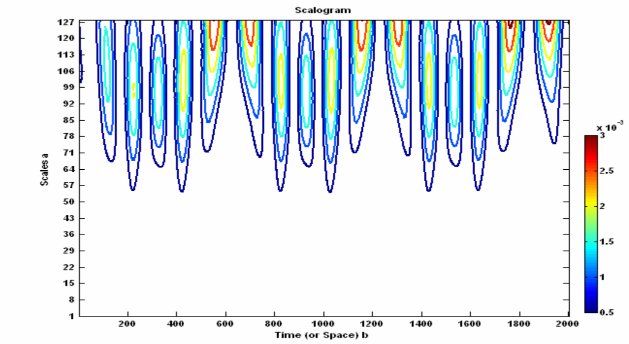


Fig.14 (a)Input signal (b) output signal (c)Spectrogram (d) Cepstrum (e) Approximation (f) Detail (g) Scalogram of 50 to 50/3 Hz matrix converter output signal.

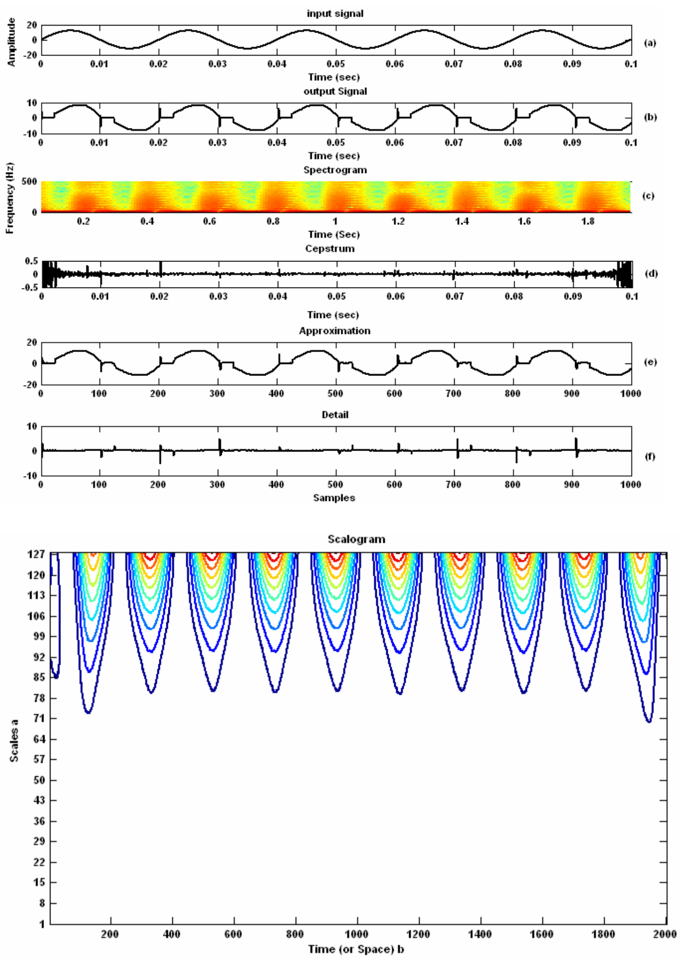


Fig.15 (a)Input signal (b) output signal (c)Spectrogram (d) Cepstrum (e) Approximation (f) Detail of 50 to 50 Hz matrix converter output signal.

TABLE II

POWER QUALITY EVENT DETECTION BY SPECTROGRAM, CEPSTRUM, WAVELET, SCALOGRAM

Sinusoidal Signal with	Spectrogram	Cepstrum	Wavelet	Scalogram
Transient	-	**Detects**	Detects	Not detecting
Swell	-	**Detects**	Detects	Detects
Sag	-	**Detects**	Detects	Detects
Interrupt	Detects	**Detects**	Detects	Detects
Flicker	-	**Detects**	Detects	Detects
Spikes in matrix converter	Detects	**Detects**	Detects	Detects
Computation time in seconds	2.124	**0.158**	0.579	2.881

VII. CONCLUSION

This paper documents an alternate method; Inverse Fourier Transform of a logarithmic spectrum called cepstrum has been used to analyze different power quality events. Its performance has been compared with other time-frequency analysis methods like spectrogram, wavelet and scalogram. The MATLAB simulation of different power quality events like sag, swell, transient, interrupt, flicker and matrix converter concludes that complex cepstrum can detect the change in amplitude, frequency and phase accurately compared to other methods with less computational time, but cannot specify quantitatively that the change is due to amplitude, frequency or phase. The future contribution will be in the implementation of cepstrum in field programmable gate arrays.

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