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Performance of Modified S-Transform for Power Quality Disturbance Detection and Classification

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Abstract

Detection and classification of power quality (PQ) disturbances are an important consideration to electrical utility companies and many industrial customers so that diagnosis and mitigation of such disturbance can be implemented quickly. Power quality signal consists of stationary and non-stationary events which need a robust signal processing technique to analyse the signals. In this paper, Modified S-Transform (MST) was used to analyse single and multiple power quality signals. MST is a modified version of S-transform with improved time-frequency resolution. The power quality signals that are considered in this study are voltage swell, sag, interruption, harmonic, interharmonic, transient, sag plus harmonic and swell plus harmonics. The performance of the proposed method has been studied under noisy and unnoisy condition. Hard thresholding technique has been applied with MST while analysing noisy PQ signals. The result shows that MST is able to give higher classification rate with better time and frequency distribution (TFD) spectrum of the PQ disturbances.

Keywords*: detection and classification, power quality disturbances, MST, time and frequency distribution*

1. Introduction

The increased requirements for supervision, control, and performance in modern power systems make power quality monitoring a common practice for utilities. With the growth of the number of monitors installed in the system, the amount of data collected is growing; making the individual inspection of the entire wave shapes no longer an option [1]. Interests in fast disturbances detection have resulted to special requirements for PQ monitoring equipment and invented a necessity for sophisticated software to automatically analyse the monitored data. As far as PQ monitoring, mitigation, protection, and control in power system are concerned, an accurate measurement in real-time circumstances for power distribution is extremely crucial and important [2]. PQ signal consists of stationary and non-stationary components. In the analysis of the nonstationary signals, one often needs to examine their time-varying spectral characteristics. Since time-frequency representations (TFR) indicate variations of the spectral characteristics of the signal as a function of time, they are ideally suited for nonstationary signals [3]. The Fast Fourier transform (FFT) and the short time Fourier Transform (STFT) are the most used techniques for detection and classification for different types of PQ disturbance occurred in power system [4]. Nevertheless, they are also several other signal processing techniques can be applied for a similar purpose. FFT is usually used to analyse harmonics in the signal. The information given are mainly in the frequency spectrum only, which make it unsuitable to analyse PQ signal which consists of transient. On the other hand, time information is also required. STFT had been introduced to overcome the inadequacy of FFT. It uses a fixed analysis window but has a major disadvantage that there is a compromise between time and frequency resolution [5]. S-transform was then introduced by Stockwell et all in 1996. The S-transform is a time-frequency spectral localisation method, similar to the short-time Fourier transform (STFT), but with a Gaussian window whose width scales inversely, and whose height scales linearly with the frequency [6]. The scaling property of the Gaussian window is

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reminiscent of the scaling property of continuous wavelets [7], however, it is not categorised in wavelet group. Due to its characteristic, S-transform has been reckoned as an algorithm which is conceptually a hybrid of short-time Fourier analysis and wavelet analysis, containing of both elements but falling entirely into neither category [8].

Several researchers have proposed a few variants of Stockwell transform by adjusting and modifying its Gaussian window function. Masinha et. al (1997) have proposed of adding parameter γ_{GS} to the standard deviation of the Gaussian window [7]. By doing this, the user will be able to specify the time and frequency resolution of S-transform on its time-frequency plane. In 1999, Mc Fadden et. al. proposed a generalised S-transform which includes windows which are asymmetrical. They applied an asymmetrical window to decomposition and analysis of gearbox vibration data in mechanical engineering [9]. Another generalised S-transform is presented by Pinnegar et. al [8] which is stated as the extension of Mc Fadden generalised S-transform, that is to include windows which have complicated scaling properties, including frequency-dependent shape. In the same year, the same author proposed to use generalised S-transform with the bi-Gaussian window which shows remarkable performance for time series sharp onset event. In 2012, Assous et al. have proposed a Modified S-Transform, where he introduced new parameters that able to control the scale and shape of the analysing window [10]. The proposed parameter able to gives a better time and frequency resolution of S-transform, and at the same time determine the phase synchrony of electroencephalogram (EEG) seizure signal using the cross-MST technique. In this paper, the Modified S-Transform has been used to analyse the PQ disturbance signal in noisy and unnoisy condition. Several signal indices have been generated based on the TFD of the MST. Features of each PQ disturbance signal are then constructed from the generated signal indices. Thus, the capability of the studied method is shown in its classification rate.

2. Modified S-Transform

The standard S-transform which has been proposed by Stockwell et. al in 1996 is given as follow [11]:

$$S(t,f) = \int_{-\infty}^{+\infty} x(t)g(t-\tau,f)e^{-j2\pi f\tau}d\tau \tag{1}$$

where $g(t-\tau,f)$ is the Gaussian window function of the S-transform. The Gaussian window function was generated with the assumption that the window's width, σ is proportionate to the inverse of frequency, f. Thus the window function of standard ST is given as follow:

$$g(t-\tau,f) = \frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(t-\tau)^2}{2\sigma^2}} = \frac{|f|}{\sqrt{2\pi}}e^{\frac{-f^2(t-\tau)^2}{2}} \tag{2}$$

In 1997, Masinha et. al have proposed a generalised ST which introducing a new constant, γ_{GS} in equation $\sigma(f)$so that the frequency resolution of ST can be adjusted accordingly [7]. The new σ is given by:

$$\sigma(f,\gamma) = \frac{\gamma_{GS}}{|f|} \tag{3}$$

The parameter γ_{GS} denotes the set of parameters that determine the shape and properties of the window function. Parameter t controls the position of the generalized window on the time axis. Higher values of γ_{GS} will give better frequency resolution of ST, but reduce its time resolution. With the new parameter, the Gaussian window function can be written as:

$$g(t-\tau,f) = \frac{|f|}{\gamma_{GS}\sqrt{2\pi}}e^{\frac{-f^2(t-\tau)^2}{2\gamma_{GS}^2}} \tag{4}$$

The value of γ_{GS} which proposed by Masinha et. al is a constant value, which is an integer values that larger than unity [7]. For modified S-transform, Assous et. al has proposed to scale the parameter γ_{GS} so that the Gaussian window function of S-transform can vary linearly with frequency [10]. The modified γ_{GS} is given as bellow:

$$\gamma_{GS}(f) = mf + k \tag{5}$$

where m is the slope and k is the intercept for a linear change in frequency. By using the new γ_{GS} formula, the modified S-transform becomes:

$$MST(t, f, m, k) = \int_{-\infty}^{+\infty} x(t) g(t - \tau, f, m, k) d\tau \tag{6}$$

where $g(t - \tau, f, m, k)$ is the window function of MST. The equation is stated as below:

$$g(t - \tau, f, m, k) = \frac{|f|}{(mf + k)\sqrt{2\pi}} e^{\frac{-f^2(t-\tau)^2}{2(mf+k)^2}} \tag{7}$$

The MST new window function also satisfies the normalization condition and hence it is invertible [10]. The value of *m* and *k* has been selected by Assous et. al. empirically. *m* is defined as four times the variance of the signal *x(t)* and value of *k* is 1 *N*, where *N* is the total samples points in a signal [10]. In this study, the value of *m* and *k* will remain the same as suggested by Assous et. al.

3. Power Quality Disturbance Signal Model

The PQ disturbance signals have been simulated based on the signal model proposed by Abdullah et al [12]. The signals are divided into three categories: voltage variation, waveform distortion, and transient signal. The model of each signal categories is formed based on IEEE Standard 1159-2009 [13]. The equations are given as:

$$z_{vv}(t) = e^{j2\pi f_1 t} \sum_{K=1}^{3} A_K \prod(t - t_{K-1}) \tag{8}$$

$$z_{wd}(t) = e^{j2\pi f_2 t} + Ae^{j2\pi f_2 t} \tag{9}$$

$$z_{trans}(t) = e^{j2\pi f_1 t} \sum_{K=1}^{3} \prod_K (t - t_{K-1}) + Ae^{-1.25(t-t_1)/(t_2-t_1)} e^{j2\pi f_2 (t-t_1)} \prod_2 (t - t_1) \tag{10}$$

where

$$\prod_K = \begin{cases} 1 & 0 \ll t \ll t - t_{K-1} \\ 0 & elsewhere \end{cases} \tag{11}$$

$z_{vv}(t)$ represent voltage variation signal, z_{wd} represents waveform distortion signal and $z_{trans}(t)$ represent transient signal. The PQ disturbance which falls in voltage variation signals are voltage sag, voltage swell and voltage interruption. Interharmonic and harmonic signal fall under waveform distortion signal. Transient signal was modeled by by $z_{\text{trans}}(t)$ equation. In these equations, K is the signal component sequence, A_K is the signal component amplitude, f_1 and f_2 are the signal frequency, t is time while $\prod(t)$ is a box function of the signal. In this analysis, f_1, t_0, t_1 and t_3 are set at 60 Hz, 0 s, 0.05 s and 0.1666 s, respectively. The introduced parameters in each signal are generated randomly in the adequate intervals in order to generate 100 realizations of each class of signals. Others parameters are defined as follow:

1. Voltage sag: $A_1 = A_3 = 1$pu , 0.1pu ≤ A_2 ≤ 0.9pu and 0.05s< t_2 < t_3
2. Voltage swell: $A_1 = A_3 = 1$pu , 1.1pu ≤ A_2 ≤ 1.8pu and 0.05s< t_2 < t_3
3. Voltage interruption: $A_1 = A_3 = 1$pu , 0pu< A_2 <0.1pu and 0.05s< t_2 ≤ t_3
4. Harmonic: A=0.02pu , f_2 =(2n)*60 Hz where n=1,2,3,...,50 .
5. Interharmonic: A=0.02pu, f_2 =(x* f_1 /10)+ f_H where 1 ≤ x ≤ 8 and f_H is even harmonic frequency component.
6. Transient: 0<A ≤ 4pu , 65Hz ≤ f_2 <5000Hz and 0.3ms< $t_2 - t_1$ <50ms

The multiple PQ disturbance signals are generated by combining the two single PQ signal model. For this research, the multiple PQ disturbances signals are the swell plus harmonic signal and sag plus harmonic signal. The equation can be stated as:

$$z_{swellhar}(t) = z_{vv(swell)} + z_{wd} \quad (12)$$

$$z_{saghar}(t) = z_{vv(sag)} + z_{wd} \quad (13)$$

In this research, the generated PQ disturbances signals are a single phase sinusoidal voltage with nominal amplitude of 1 p.u. and phase 0 radians. Each PQ disturbance signal consists of 10 cycles and each cycle consists of 256 sample points. The sampling frequency is 15.36 kHz.

4. Power Quality Signal Indices and Features Construction

The time-frequency distribution is employed to generate a set of indices which are used in the classification process. The indices are extracted from the parameters of the signal. In this study, the parameters of the signal obtained from optimized TFR are the instantaneous values of RMS voltage, RMS fundamental voltage, total harmonic distortion (THD), total non-harmonic distortion (TnHD), total waveform distortion (TWD). The instantaneous RMS voltage can be defined as below:

$$V_{rms}(t) = \sqrt{\int_0^{f_{max}} |MST_x(t,f)|^2 df} \quad (14)$$

f_{max} is the maximum frequency that being considered in MST. Instantaneous RMS fundamental voltage is defined as the RMS voltage at power system frequency [12]. It can be calculated as:

$$V_{1rms}(t) = \sqrt{\int_{f_L}^{f_H} |MST_x(t,f)|^2 df} \quad (15)$$

where f_H is the frequency when the lobe of fundamental frequency end, and f_L is the frequency at the starting point of the fundamental frequency lobe. Waveform distortion represents all deviations of the voltage waveform from the ideal sinusoidal waveform in terms of magnitude or frequency the signal [9,14]. The instantaneous total waveform distortion can be expressed as:

$$TWD(t) = \frac{\sqrt{V_{rms}(t) - V_{1rms}(t)}}{V_{1rms}(t)} \quad (16)$$

where $V_{1rms}(t)$ is the instantaneous RMS fundamental voltage and $V_{rms}(t)$ is the instantaneous RMS voltage. Total harmonic distortion, THD is used to measure of how much harmonic content in a signal [9,15]. It and can be defined as:

$$THD(t) = \frac{\sqrt{\sum_{h=2}^{H} V_{h,rms}(t)^2}}{V_{1rms}(t)} \quad (17)$$

where $V_{h,rms}(t)$ is the RMS harmonic voltage and H is the highest measured harmonic component. While total non-harmonic distortion which is used to characterized the existence of interharmonics components can be calculated as:

$$TnHD(t) = \frac{\sqrt{V_{rms}(t)^2 - \sum_{h=0}^{H} V_{h,rms}(t)^2}}{V_{1rms}(t)} \quad (18)$$

The instataneous frequency, $IF(t)$, of the signals were determined based on maximum peak of the MST matrix in the frequency spectrum for each sampling time, t s . The equation is given as follow [16]:

$$IF(t) = arg\left[\max_{f \in Q_f} \Lambda(t,f)\right] \quad (20)$$

with $Q_f = \{ f : 0 \leq f \leq f_{max} \}$ being a basic interval along the frequency axis.

Feature extraction, which is a mapping process from the measured signal space to the feature space, can be regarded as the most important step for automatic PQ signal detection and classification system. In this study, Support Vector Machine (SVM) with radial basic function (RBF) kernel has been selected as the classification algorithm. Several signal's features have been extracted for training and testing data set of the classification algorithm. The extracted features are:

1. Minimum magnitude of instantaneous RMS voltage, F1.
2. Maximum magnitude of instantaneous RMS voltage, F2.
3. Minimum magnitude of instantaneous RMS fundamental voltage, F3.
4. Maximum magnitude of instantaneous RMS fundamental voltage, F4.
5. Magnitude difference of instantaneous RMS voltage, F5.
6. Magnitude difference of instantaneous RMS fundamental voltage, F6.
7. Average total harmonic distortion, F7.
8. Average total non-harmonic distortion, F8.
9. Average total waveform distortion, F9.
10. Maximum magnitude of instantaneous total harmonic distortion, F10.
11. Maximum magnitude of instantaneous total non-harmonic distortion, F11.
12. Maximum magnitude of instantaneous total waveform distortion, F12.
13. Minimum magnitude of instantaneous total harmonic distortion, F13.
14. Minimum magnitude of instantaneous total non-harmonic distortion, F14.
15. Minimum magnitude of instantaneous total waveform distortion, F15.
16. Magnitude difference of instantaneous total harmonic distortion, F16.
17. Magnitude difference of instantaneous total non-harmonic distortion, F17.
18. Magnitude difference of instantaneous total waveform distortion, F18.
19. Instantaneous frequency, F19.

5. Results and Analysis

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2,5]. The discussion can be made in several sub-chapters.

5.1. MST Spectrum versus ST Spectrum

In this study, the performance of the MST was first being analysed from the time-frequency spectrum that it can be generated with three (3) signal models that being used in this study, which are voltage variation, waveform variation and transient signal model. The MST spectrum is then compared with the spectrum generated by the standard S-transform (ST). The standard ST was simulated by setting the value of γ_{GS} (*f*) in MST Gaussian window's equation equal to 1. By doing this, the resulted window function of MST will be the same as standard ST window function which is given in Eq. 1.

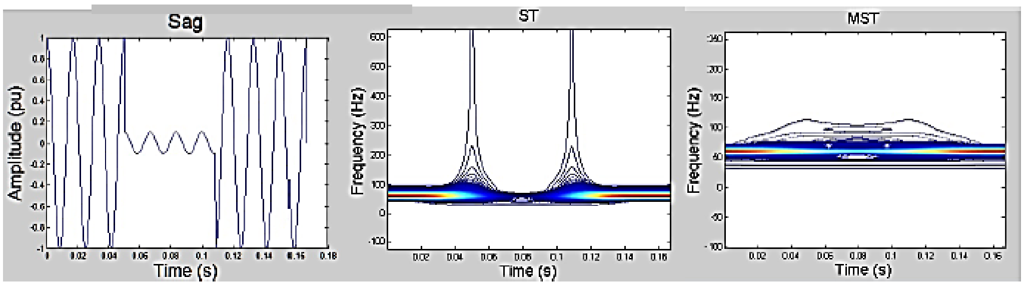
The resulted spectrums of the three signal models are shown in Fig. 1 in a contour plot graph. From the TFD shown in Fig. 1, it is observed that MST gives excellent frequency information for voltage variation signal, waveform distortion signal, as well as transient signal. The frequency spectrum in MST has less smearing contour as compared to standard ST's TFD. We can also see in Figure 1 that the detection of interharmonic and harmonic frequency components was substantial in MST's TFD. However, in terms of temporal resolution, the MST showing less precise detection as compared to standard ST.

5.2. MST Spectrum and Signal Indices

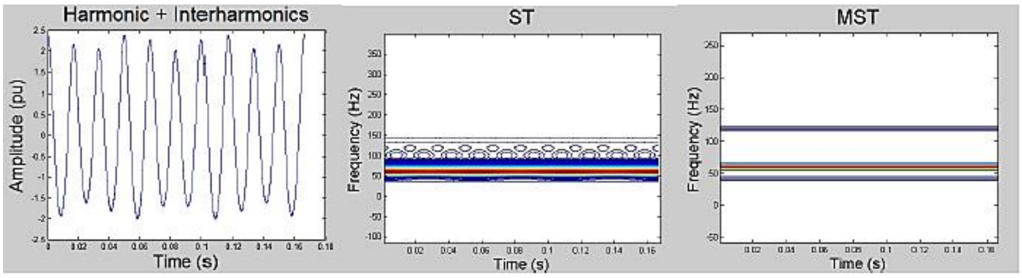
Eight (8) types of PQ disturbance signal have been analysed using MST in this research. The PQ disturbances are voltage sag, swell, interruption, transient, even harmonic, interharmonic, sag plus even harmonic and swell plus even harmonic. The resulted spectrums for voltage sag, voltage transient and harmonic plus interharmonic signal, as well as the resulted signal indices are shown in Figure 1 - 3 respectively.

From the result, it is observed that the resulted TFD from MST is able to display the existence of the PQ disturbances in the input signal. For voltage sag signal, the highest peak of the MST's TFD contour occurs at the frequency of 60 Hz, and the peak magnitude reduces in the middle of the time plane, showing a drop of the magnitude of the input signal during the given time. The contour, however, remains in the same frequency of 60 Hz while the magnitude drop occurs. This shows that the analysed signal is having a change in the magnitude only, not in its frequency. The signal's indices, which consist of the instantaneous RMS voltage, instantaneous RMS fundamental voltage, instantaneous THD, instantaneous TnHD, and instantaneous TWD were also giving the correct information about frequency and magnitude condition of the analysed signals. These mean that correct features can be obtained from the extracted indices of the resulted MST time-frequency distribution.

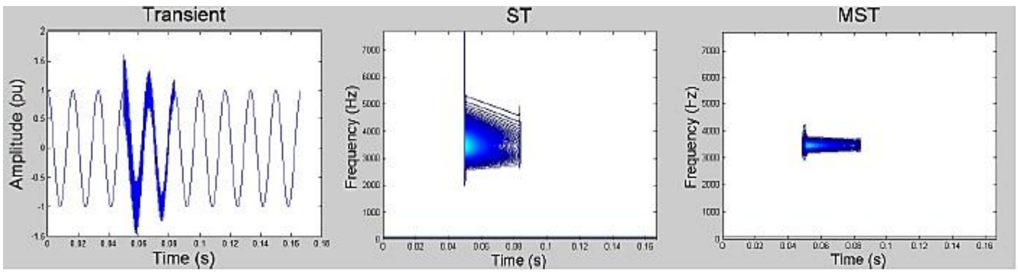
As for transient signal, the resulted TFD from MST matrix in Figure 2(b) shows an abrupt change in signal frequency for a specific duration. For this signal, the transient frequency that has been generated is 3458 Hz, which is exactly as depicted in the transient TFD of MST matrix. The magnitude of the transient signal, however, cannot be estimated from the MST contour plot. It can be estimated from the curve of the instantaneous RMS fundamental signal, where we can see the increment of RMS voltage magnitude. The signal indices of transient are also able to give the correct features which will help the classification system to perform well.



(a)



(b)



(c)

Figure 1. Time and frequency spectrum of ST and MST for (a) voltage variation signal, (b) waveform variation signal and (c) transient

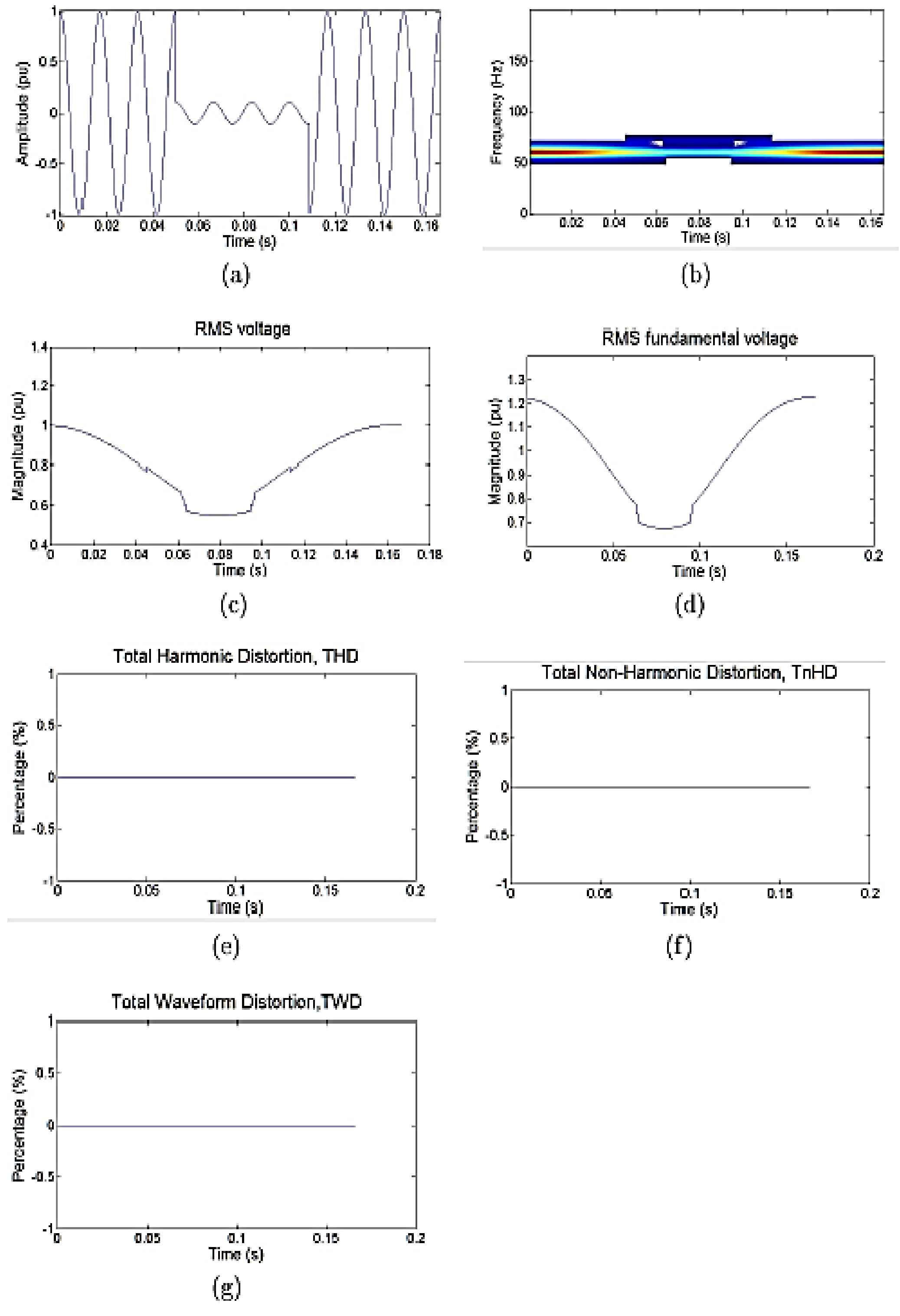


Figure 2. (a) Voltage sag signal construction, (b) MST time-frequency distribution, (c) Instantaneous RMS voltage, (d) Instantaneous RMS fundamental voltage, (e) Instantaneous THD, (f) Instantaneous TnHD and (g) Instantaneous TWD for voltage sag

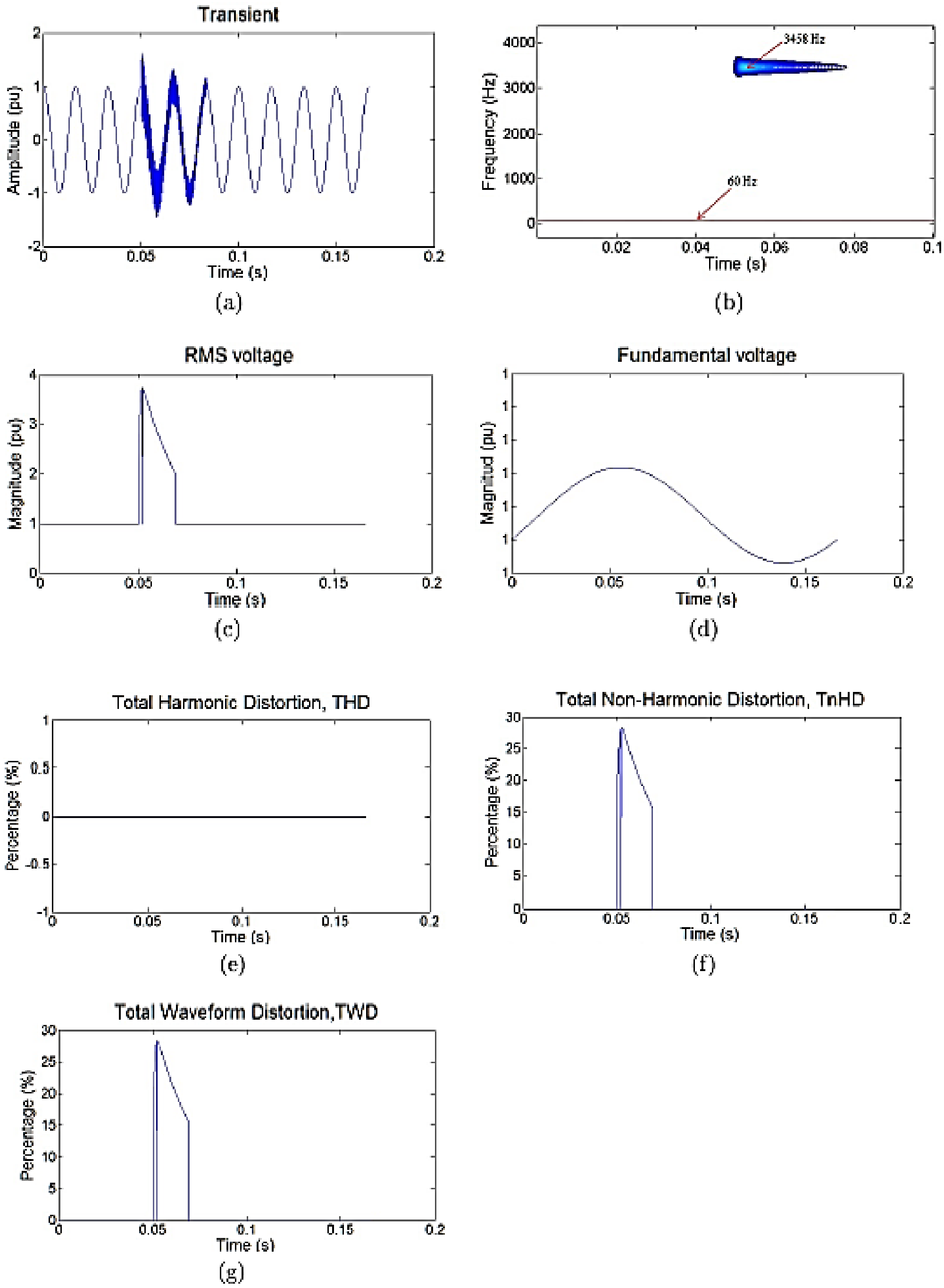


Figure 3. (a) Transient signal construction, (b) MST time-frequency distribution, (c) Instantaneous RMS voltage, (d) Instantaneous RMS fundamental voltage, (e) Instantaneous THD, (f) Instantaneous TnHD and (g) Instantaneous TWD for voltage swell signal

5.3. Power Quality Classification using SVM

Support Vector Machines (SVM) is a powerful technique for rectify problems in nonlinear classification, function estimation, and density estimation in kernel based methods in general [17,18]. In this study, RBF support vector machine (RBF SVM) were utilised to classify all these eight types of PQ disturbances. More steps on analysing the PQ disturbance signal were further proceeded by generating 100 signals of each type from the 8 classes of PQ disturbance signal using Equations (8) - (10) using Matlab R2012a. The description of the classes of the power quality disturbances to be predicted by the SVM is shown in Table 1. To obtain the outcome, the training and testing data were divided by using 1/3 distribution, indicating that 2/3 of the generated signals will be used for training, and the rest will be used as testing data. A total of 19 features*100 signals were extracted from each class of simulated PQ signals. By using five cross-validation technique, the optimised value of C and γ was determined iteratively. In order to verify the robustness of the proposed method, detection and classification of PQ signals added with a random white Gaussian noise (AWGN) of zero mean and signal to noise ratio (SNR) varying from 50dB to 10dB was observed. The results are shown in Table 2 and 3.

Table 1. Description of Classes of PQ Disturbances

Type of PQ Disturbances	Classes
Voltage sag	C1
Voltage swell	C2
Voltage interruption	C3
Oscillatory transient	C4
Interharmonics	C5
Even harmonic	C6
Sag + even harmonic	C7
Swell + even harmonic	C8

Table 2. Classification Rate for the PQ Disturbance Signal Without the Presence of Noise

	C1	C2	C3	C4	C5	C6	C7	C8	Classification rate (%)
C1	32	0	1	0	0	0	0	0	97
C2	0	33	0	0	0	0	0	0	100
C3	0	0	33	0	0	0	0	0	100
C4	0	0	0	33	0	0	0	0	100
C5	0	0	0	0	33	0	0	0	100
C6	0	0	0	0	0	33	0	0	100
C7	0	0	0	0	0	0	33	0	100
C8	0	0	0	0	0	0	0	33	100

Average classification rate: 99.7%

Table 3. Classification Rate for The PQ Disturbance Signal with the Presence of Noise

SNR of AWGN (dB)	Classification rate (%)
50	98
40	98
30	98
20	98
10	92

From the result shown in Table 2 and 3, it is observed that the combination of MST with RBF kernel SVM is able to give a higher classification rate for detection and classification of single and multiple PQ disturbance signals. As for the noisy PQ disturbance signal, the classification rate is almost constant at 98% for 50dB until 20dB range of SNR of AWGN, and almost 92% of classification rate for 10dB SNR of AWGN. This shows that MST is suitable for the PQ disturbance signal features extraction and can be used in the real-time automatic PQ disturbance signal analysis system.

6. Conclusion

In this paper, a new signal processing method which is known as MST is studied for the application of automatic PQ disturbance detection and classification system. Nineteen (19) signal features have been proposed and extracted from each signal of each class of PQ disturbance signals. The result obtained is remarkably high, in which almost 100% classification rate is achieved for clean PQ disturbance signals. The performance of the method was also analysed in noisy corrupted disturbance signal. The resulted classification rate for the noisy corrupted signal (SNR = 10 dB) gives higher percentage values above 92%. As for higher SNR values (50 dB to 20 dB), the result is almost constant at 98%. From this result, we can conclude that the studied method is a robust method to analyse PQ disturbance signal in noisy and unnoisy environments. It is also concluded that the extracted features proposed in this paper are able to characterise each type of disturbance into a unique and detectable manner.

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