Detection and Classification of Power Quality Events using DWT and MSD

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***Abstract*—In power system the electrical signals always have some disturbances and discontinuities. The advanced technological world demands electric power which is free from any disturbance. Many of these problems such as equipment failure, and low response of equipment are the results of the disruption of the electric power supply. Computer based processes or automatic system fails to operate due to these power disturbances. Hence, detection and classification of these power quality events is necessary to avoid such incidents. In this paper, nine classes of power quality (PQ) events are detected by applying discrete wavelet transform (DWT) and multi-resolution signal decompo- sition (MSD). DWT coefficients based approach for the energy contents in the different frequency zone is proposed for the classification of PQ disturbances. The coefficients at each levels are used for extracting the features of various disturbances. Classification is done on the basis of DWT and MSD with these extracted features. Features extracted using DWT coefficients have important role for classifying different PQ disturbances. Several simulations for detection and classification of these PQ events based on MSD and DWT are performed. Classification of all nine events is shown to demonstrate the effectiveness of proposed method.**

Keywords - Discrete wavelet transform, Multi-resolution signal decomposition, Power quality disturbance.

I. INTRODUCTION

Power quality can be defined depending on one's frame of reference for e.g. end customer, utility and manufacturer etc. According to [1] power quality can be, any power problem manifested in voltage, current or frequency deviations that results in failure or mis-operation of customer equipment. The quality of electricity supplies has become a major concern of end customers and electric utilities. The most of power electronics devices may fail to sustain sudden drop in voltage and stops working. In order to avoid these losses in any system, power quality disturbance must be detected and localized. Wide use of power electronic equipment such as adjustable speed drives, programmable logic controllers (PLC's), converters, converter-driven equipment etc. fails to maintain power quality. Many end users and customers of power supply faces a great challenge due to voltage sags, switching transients, notches, flicker and harmonics. Most of these power quality events cause short and long duration events according to severity of the fault. Reliability and quality of power supply is major issue and need to be maintained. Still there are some technical challenges for understanding the behavior of these disturbances occurred in the system [2].

Power system stability is highly dependent on load which is dominantly varying in nature. This leads to create unwanted disturbances in the power networks. In the field of identification as well as mitigation of signal disturbances wavelet transform is widely used. Wavelet transform (WT) is gaining importance in power system disturbance analysis since past 20 years [3]. Also this paper gives an extensive review and mathematical background of wavelet transform for analyzing behavior of power system dynamics. A critical review on application of various feature extraction techniques for classification of PQ events is given in [4]. Earlier Fourier transform was used for the estimation of the magnitudes of the fundamental and harmonic components in the system. FT is used for analysis of stationary signals as well as non-stationary signals. FT applied to non-stationary signals produces erroneous results. Different signal processing tools have been proposed to overcome the limitations of the standard methods, such as the short-time Fourier transform (FT), kalman filtering (KF), wavelet transform. Moreover, an on-line implementation of wavelet based system for detection of various events is proposed in [5]. H. Mokhtari *et. al.* presented on-line detection of voltage events using wavelet transform. Various signal processing techniques are used for the feature extraction of the PQ disturbances. These PQ disturbances are then classified to specific class using various intelligence techniques like, artificial neural network (ANN), fuzzy logic, support vector machine etc. [6].

A PQ classification based on WT with genetic algorithm is given in [7]. FT has been extensively used for analyzing the frequency contents of the signals. Besides, the FT is not an efficient analyzing tool for extracting the transient information of the non-stationary signals [8]. Also D.Yong *et.al.* proposed an algorithm for automatic classification of power quality disturbances using WT and SVM. Detection and classification of these power quality disturbances is of major issue since last two decades. Hence, there is widespread use of various intelligent techniques for the classification of these PQ disturbances [9]. Different classification techniques with % of classification of accuracy is given in [10], [11].

This paper presents DWT-MSD based approach for detection and classification of PQ events. These events are classified using DWTC combined with % energy entropy to have better classification accuracy. The paper is organized as follows. Mathematical concepts of wavelet transform (WT) are given in Section II. Section III gives the detection and feature extraction of all the PQ events using DWT and MSD. Classification of the PQ disturbances is given in Section IV. Section V presents conclusion based on the simulation results.

I. WAVELET TRANSFORM

Wavelet transform is capable of providing time-frequency localization of the disturbed waveform. All the wavelet functions are the transformations derived from mother wavelet through the shifting (translation) and scaling (dilation or compression). WT can be classified as, continuous wavelet transform (CWT) and DWT. CWT of a signal x(t) is given by eq. with respect to the mother wavelet g(t) is defined by,

$$x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) g(\frac{t-b}{a}) dt, \qquad (1)$$

where a is the dilating or scale factor and b is the translation factor. Thus $g(\frac{t-b}{a})$ is obtained through shifting and scaling by a factor b and a respectively. Scale is defined as reciprocal of frequency. Scaling either dilates (expands) or compresses a signal. Larger the scale (lower frequencies) expands signal and provide detailed information hidden in the signal. Smaller the scales (high frequencies) compress the signal and provideglobal information of the signal.

The CWT was developed as advanced approaches to the STFT to overcome the resolution problem. CWT can be practically computed by analytical equations, integrals etc. increase the substantial redundancy. Hence to avoid this DWT is used to discretize a technique. DWT is used to decompose a discretised signal into different resolution levels reducing the computational time. Mathematical relation for mother wavelet is given by,

$$g_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} g(a_0^{-m} t - n b_0) \qquad (2)$$

DWT is given by,

$$x(m,n) = \sum_t x(t) g\left(\frac{t - n_0 a_0^m}{a_0^m}\right) dt. \qquad (3)$$

Mother wavelet (2) is translated and dilated discretely by selecting scaling factor Mother Wavelet (2) is translated and dilated discretely by selecting scaling factor $a = a_0^m$ and translation factor $b = nb_0a_0^m$, where a_0 and b_0 are fixed constants with $a_0 > 1, b_0 > 0$. Here, m and n are scaling and sampling numbers respectively. Appropriate choice of a_0 and b_0 gives multi-resolution analysis (MRA). In MSD, wavelet function *(ψ)* generates the detail coefficients and scaling function generates approximation coefficients of the decomposed signal. The wavelet function and scaling function *(φ)* are as followed,

$$\psi_{j,n}(t) = 2^{j/2} \sum_n d_{j,n} \psi(2^j t - n) \qquad (4)$$

$$\phi_{j,n}(t) = 2^{j/2} \sum_n c_{j,n} \psi(2^j t - n), \qquad (5)$$

where, *dj* is the detailed and *cj* is the approximated coefficients at scale *j.* Let *x(n)* be discrete signal. MRA technique for signal decomposition uses high pass and low pass filters. Outputs of these high pass *(g(n))* and low pass *(h(n))* filters are

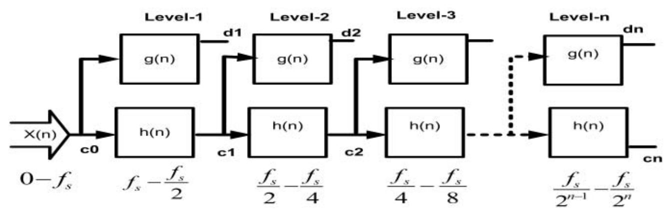

Fig. 1. Typical three level MRA with DWT.

detailed *(dn)* and approximated *(cn)* coefficients respectively as shown in Fig. 1. Where, fs is the sampling frequency. The decomposed signals at scale 1 are d1 and c1. The approximation coefficients are again fed to low pass and high filters as shown in Fig. 1. The detailed and approximated coefficients are obtained recursively in the same way for all decomposition levels from input signal. These wavelet coefficients of the sampled signal, x(n), decomposed by the L-scale MSD can be expressed using following equation:

$$\begin{aligned} d_j(n) &= \sum_{k=1}^{N} x(n) h_j(k - 2^j n) \quad j = 1, 2, \ldots\ldots\ldots L \\ c_L(n) &= \sum_{k=1}^{N} x(n) g_L(k - 2^L n) \end{aligned} \qquad (6)$$

Where *dj(n)* represents detailed coefficient of signal at level *n* and $c_L(n)$ is the approximation coefficients at the last scale. *L,* h_j, g_L denote the impulse responses followed by filtering in the MSD. N is the number of sampled data in a finite interval. Since the family of dilated and shifted wavelets constitutes an orthogonal basis, it is then possible to exactly reconstruct the original signal from its coefficients, given by,

$$x(n) = \sum_k \left(\sum_{j=1}^{L} d_j(n) h_j(k - 2^j n) + c_L(n) g_L(k - 2^L n) \right)$$

III. DETECTION AND FEATURE EXTRACTION OF PQ EVENTS

A. Introduction

The PQ disturbances consist of both the stationary and non-stationary signals like the voltage interruption, sag, swell, spike, harmonic with sag etc. In this paper, nine types of different disturbances alongwith the pure sine wave are considered for classification and detection. These PQ events are analyzed with 50 Hz fundamental frequency and 12.8 kHz sampling frequency. Following Table I shows the expression models for all the disturbances of PQ. These PQ events are created using Mathworks MATLAB software [12]. PQ disturbances/events cover a wide range of frequencies with significantly different magnitude variations and of stationary or non-stationary content. DWT events with MSD gives flexibility with the frequency content in the disturbed signal and hence have many more applications in the signal processing.

B. DWT Application in Detection

All the PQ events like voltage interruption, sag, swell and harmonics etc. are generated for simulation purpose using Table I. For power quality disturbance detection, disturbances can be can be classified into two categories, steady state and transient phenomena. Harmonics, voltage flickers, or periodic notches are defined by their characteristics in the steady state. Disturbances like impulses or oscillatory transients are described as transient phenomena during their short-duration. In this paper, both events i.e., steady and transient states are discussed for detection purpose. In transient case, the waveform is marked with sharp edges, abrupt and rapid changes, and has a fairly short duration. Different mother wavelets are used in signal processing application are Daubechies, Coiflets, Symlets and Haar wavelets. Daubechies wavelets have good property of extracting the features from the distorted signals. Hence, from the family of Daubechies db6 is used for signal decomposition for ten scales using db6 mother wavelet. Daubechies mother wavelet (db6) contain larger energy contents at each level has compactness, and ability to localize the event accurately. Moreover, it has shorter filter length and computational time. Using MSD, the disturbance signal can be partitioned into different resolution levels in the time-frequency domain. This can provide the ability of localizing PQ events property in the time domain and dividing the total energy of the signal into different frequency bands. The occurrence of transient event can be detected at two lower levels, d1 and d2. In particular, the first filtered signal, d1(n), contains the highest frequency components of the signal. This property can be used to detect and localize PQ events such as transients, sharp edges, or jumps in the pure power disturbances. For feature extraction of PQ event using MSD ten level of decomposition is performed. Figs. 2-8 show the three levels of discrete wavelet transforms coefficients (DWTC) for detection of all the seven events alongwith the disturbed signal. For each signal, in Figs. 2-4, short duration voltage disturbances are initiated at 315 and terminated at 644 sample points. This is accurately detected by DWT detailed signal coefficients d1 and d2, having high frequency components. In this figures signals decomposed by MSD, include information such as disturbance occurrence time, frequency components, and energy distributions. One method to extract a feature is to use the energy of the signal because PQ events give different energy distributions at each scale or level. In Figs. 5-7, harmonics, combined with sag and swell is located and detected at first two finer levels of decomposition i.e. d1 and d2 at sample points 315 and 644. In Fig. 8, transient is detected within 0.5 cycle of disturbance shown by d1 detailed coefficients.

For the MSD of ten scales the energy at the first level is the highest frequency component in the range to kHz and it represents time information of fast transient disturbance. This information would represent distinct features available to distinguish transient events from different events. However, their energy is typically very low compared to the other disturbances. Table III shows the frequency range component in the range to kHz and it represents time information of fast transient disturbance. This information would represent distinct features available to distinguish transient events from different events distribution represents time information of fast transient disturbance. This information would represent distinct features available to distinguish transient events from different events. However, their energy is typically very low compared to the other disturbances. Table III shows the frequency range distribution for the ten level energy distribution. DWTC shows the characteristics of disturbances in terms of frequency (6400-3200 Hz) using the DWT filters. Detailed coefficients d1 and d2 indicates the high frequency transients, while d3 and d4 shows the medium frequency transient characteristics of the distorted signals. Harmonics frequency range is indicated by d5 and d6 components. Reference frequency range is indicated by the d7 (100-50 Hz), while d8, d9 and d10 having low ranges of frequency. Highest energy in detail coefficients (d1-d10) indicates the given range of frequency in disturbance.

C. Feature Vector Extraction

Feature parameter represents most important characteristic of power quality disturbance. This parameter can be obtained through analyzing disturbed signal using effective technique like DWT. The signals are decomposed by a wavelet function using db6 as a mother wavelet. Signal is decomposed up to ten levels using MSD, in order to examine the feature vectors for each disturbance. Generally, most of the disturbances in a power system have short duration and small energy as well as more energy compared to the original signal. Hence, using this extracted energy; disturbance part can be separated from original signal by MSD. Hence these measures can be used as classification of these different disturbances.

TABLE I. MATHEMATICAL EXPRESSIONS FOR PQ EVENTS.

PQ events	Expressions for unity amplitude	Parameters
Normal	$\sin(\omega t)$	ω=2πf
Interruption	$\sin(\omega t)[1-\alpha(u(t-t_1)-u(t-t_2))]$	0.9< α <1.0
Sag	$\sin(\omega t)[1-\alpha(u(t-t_1)-u(t-t_2))]$	0.1< α <0.9
Swell	$\sin(\omega t)[1+\alpha(u(t-t_1)-u(t-t_2))]$	0.1< α <0.8
Oscillatory transient	$\sin(wt)+\alpha\exp(-(t-t_1)\tau)(u(t-t_1)-u(t-t_2))\sin(2\pi ft)$	0.1< α <0.8, $0.5T < t_2 - t_1$, $300Hz < f$, $8ms < \tau < 40ms$
Harmonics	$\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt)+\alpha_7\sin(7wt)$	$0.05 < \alpha_1, \alpha_5, \alpha_5 < 0.15.$
Sag+Harmonics	$[1-\alpha(u(t-t_1)-u(t-t_2))](\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt))$	0.1< α <0.9 , $0.05 < \alpha_1, \alpha_5$
Swell+Harmonics	$[1+\alpha(u(t-t_1)-u(t-t_2))](\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt))$	0.1< α <0.8 , $0.05 < \alpha_1, \alpha_5$
Noise	$100\times\sin(2\times\pi\times 8000\times t)+(1.7)\times\sin(2\times\pi\times 7799\times t)+(0.1)\times randn(size(t))$	$t = 0 : 1/f_s : 1 - 1/f_s$

TABLE II. ENERGY CONTENT IN SINE WAVE AND OTHER PQ EVENTS.

PQ Events	Ed1	Ed2	Ed3	Ed4	Ed5	Ed6	Ed7	Ed8	Ed9	Ed10	Average of DWTC at 10 levels	% Average EE of DWTC
Normal sine	0.0000	0.0000	0.0005	0.0026	0.0044	0.2388	56.9002	40.5621	0.1169	0.0744	9.790	0.0
Interruption	0.0020	0.0015	0.0053	0.0126	0.0473	0.2956	56.0373	40.5959	0.2226	0.1623	9.7382	-5.18
Sag	0.0013	0.0032	0.0049	0.0073	0.0321	0.3132	56.3512	40.4724	0.1684	0.1076	9.7462	-4.38
Swell	0.0007	0.0017	0.0027	0.0043	0.0179	0.2695	57.4430	40.4833	0.1042	0.0668	9.8394	6.95
Transient	0.0006	0.0018	0.0178	0.0442	0.0080	0.2128	47.8606	34.1002	0.1529	0.1564	8.6119	-117.81
Harmonics	0.0000	0.0003	0.0031	0.0769	6.6061	32.7238	20.2258	36.7056	0.1065	0.5154	9.6963	-9.37
Sag+harmonics	0.0108	0.0169	0.0377	0.0776	4.1836	43.1775	22.9677	15.9976	0.1997	0.2608	8.6930	-109.7
Swell+harmonics	0.0236	0.0368	0.0762	0.1303	4.7345	44.6413	24.2898	16.4982	0.2004	0.2343	9.8906	15.84
Noise	99.6289	0.0110	0.2345	0.0182	0.0014	0.0006	0.0016	0.0033	0.0060	0.0083	9.9914	20.14

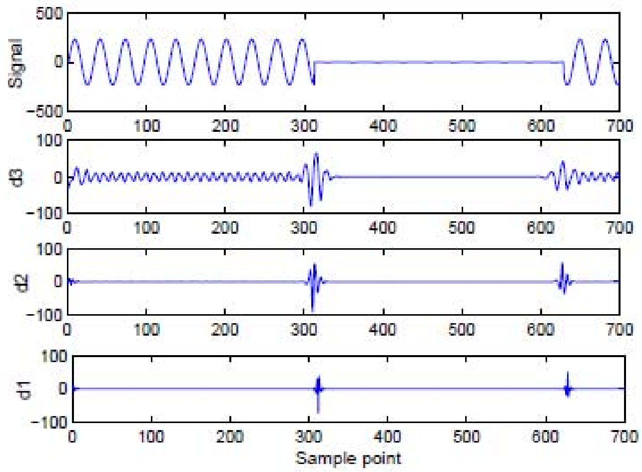

Fig. 2. 3 Level DWTC decomposition for detection of voltage interruption.

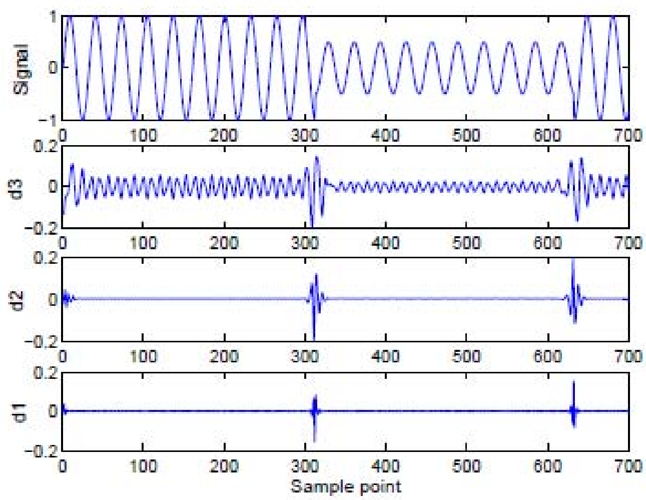

Fig. 3. 3 Level DWTC decomposition for detection of voltage sag.

In DWT, signal energy at each level of the DWTC can be separated in time domain and frequency domain. Hence the relationship between the energy in the PQ signal *x(t)* each scale of the DWTC can be calculated using the Parseval's principal, by using following equation,

$$1\Big/N\sum^{t}x(t)^2=\sum_{j=1}^{N}|A_{i,j}|^2+\sum_{j=1}^{N}|D_{i,j}|^2, \qquad (7)$$

Where i= 0,1,2.....,l. An average power of the approximated version of the decomposed signal and the detailed version of the decomposed signal is given by the Parseval's theorem. The detailed version of the signal contains significant information of the signal. This can be used to extract features from distorted PQ events. The Parseval's principal in the DWT application of signal analysis can be implemented be extracting the total energy of the discrete time domain signal. This can be done by following expression:

$$ED_i=\sum_{j=1}^{N}|D_{i,j}|^2, \qquad (8)$$

$$EA_l=\sum_{j=1}^{N}|A_{i,j}|^2, \qquad (9)$$

where i = 0,1,2.....,l.

Here, i and N are the wavelet decomposition level and the number of coefficients of the detailed signal at each decomposition level respectively. ED_i and EA_l are the energies of the detailed coefficients at decomposition level 1 and the energy of the approximate coefficients at level l respectively. The energy content in an approximated level is not considered for feature extraction. The extracted feature vector helps in distinguishing the disturbance signal from each other. For voltage distorted signal for the feature extraction ten decomposition levels are performed. Table II shows energy of detailed coefficients up to ten level for all the classes of power quality events. The average energy entropy is useful for the classification of these power quality events, as this feature extract the unwanted energy from the disturbed signal with help of original sine signal. W_{avg} is the entropy difference of average energy distribution during PQ events and pure sine wave obtained from MSD. This can be expressed by,

$$\%W_{avg}=\frac{WD_{NS}-WD_{PS}}{WD_{PS}}\times 100 \qquad (10)$$

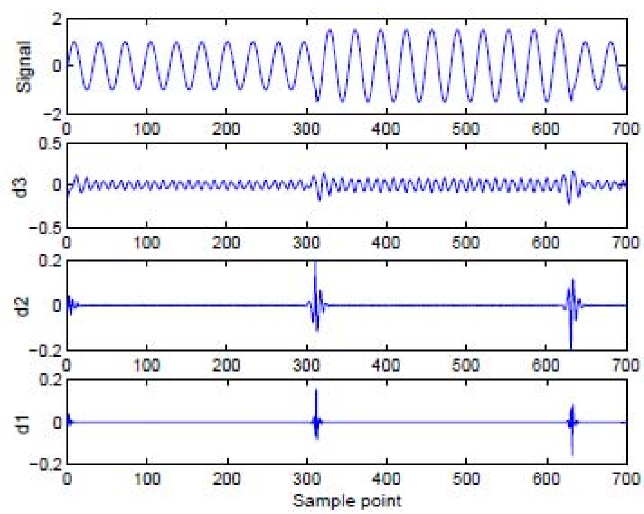

Fig. 4. 3 Level DWTC decomposition for detection of voltage swell.

TABLE III. DWT DECOMPOSITION LEVELS

Decomposition Level	DWT decomposition coefficients	Frequency range (Hz)
1	d1	6400-3200
2	d2	3200-1600
3	d3	1600-800
4	d4	800-400
5	d5	400-200
6	d6	200-100
7	d7	100-50
8	d8	50-25
9	d9	25-12.5
10	d10	12.5-6.25

Where, WD_{NS} is the average energy distribution during normal sine and WD_{DS} is the average energy distribution during PQ disturbance at all levels. Non-stationary PQ events, are always varying in nature with the frequency and gives respective energy distribution. The energy entropy (EE) is used to extract significant feature vectors from different PQ events using DWT filters.

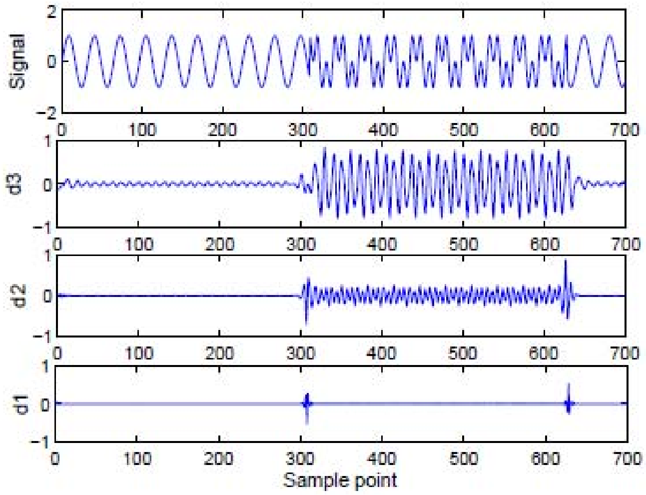

Fig. 5. 3 Level DWTC decomposition for detection of harmonics.

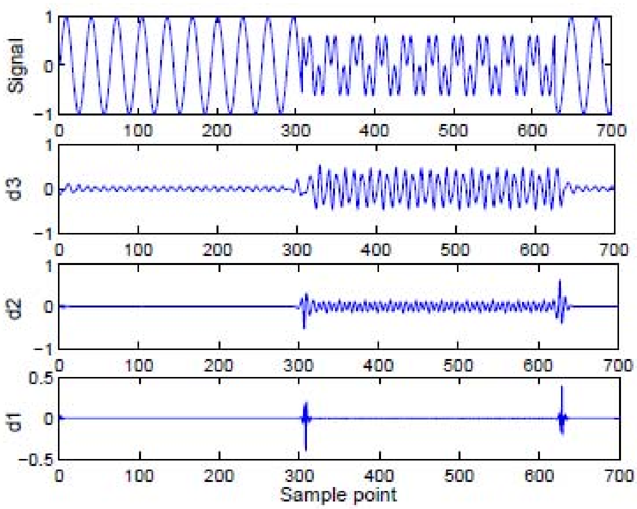

Fig. 6. 3 Level DWTC decomposition for detection of sag combined with harmonics.

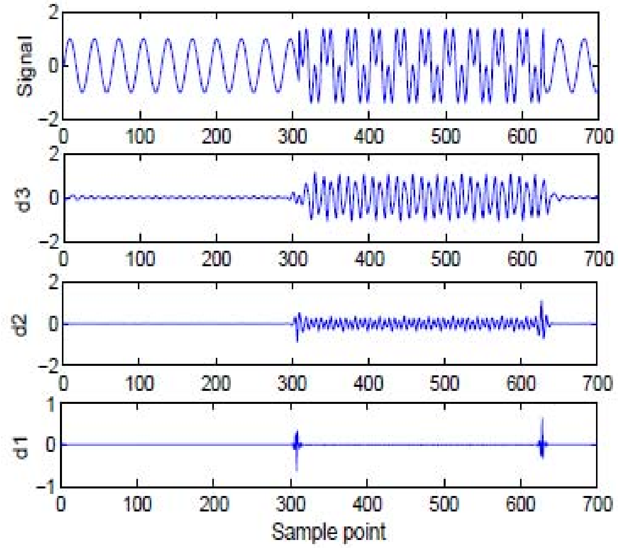

Fig. 7. 3 Level DWTC decomposition for detection of swell combined with harmonics.

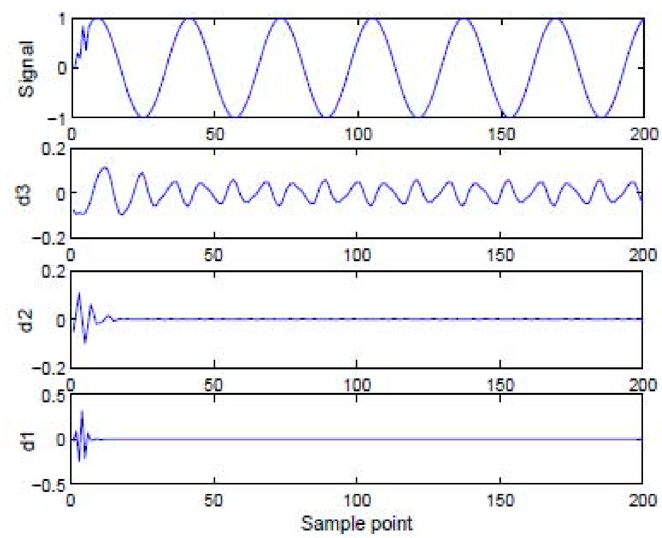

Fig. 8. 3 Level DWTC decomposition for detection of transient.

The variations in average EE for nine types of disturbance signals are analyzed using db6 mother wavelet filters for ten level of decomposition as is shown in Table II. In this Table, average of DWT coefficients as well as % EE of DWTC is given.

IV. CLASSIFICATION OF PQ EVENTS USING DWT

DWT decomposes the captured signal into a group of different frequency levels, each corresponding to a particular frequency band. Therefore, the wavelet technique discriminates disturbances from the pure signal, and then analyses them separately. The discontinuity in the signal due to disturbed sharp edges, transitions and jumps are reflected in the higher frequency zone. Thus any change in the smoothness of signal can be detected and localized at the finer resolution level. The wavelets coefficients of the finer resolution level will have high magnitude at the start and the end point of disturbance. The proper feature vector extraction is the key points for an efficient classifier performance. DWT based detailed coefficients energy extracted from the PQ disturbance is used for the characterization and classification of these events. This DWTC's detailed coefficients energy (d1-d10) extracted using MRA's filter. An MRA curve curve for comparison of energy level in pure sine wave and other power quality events using MSD is shown in Fig. 9. The PQ disturbances such as swell, swell+harmonics, noise has the highest ranges of energy distribution due to its high magnitude. DWTC (d1-d5) indicates high frequency range and respective d5-d6 low frequency range. High frequency PQ disturbances and low frequency disturbances are easily separated by this MRA curve.

According to Table II the classification bar chart based on this percentage energy entropy is shown in Fig. 10 for ten types of power quality disturbances. The classification of PQ disturbances is done on the basis of percentage energy entropy of DWTC and average absolute sum of DWTC. The variation in energies for different PQ events based on the wavelet filters gives the features to identify the events and to classify them.

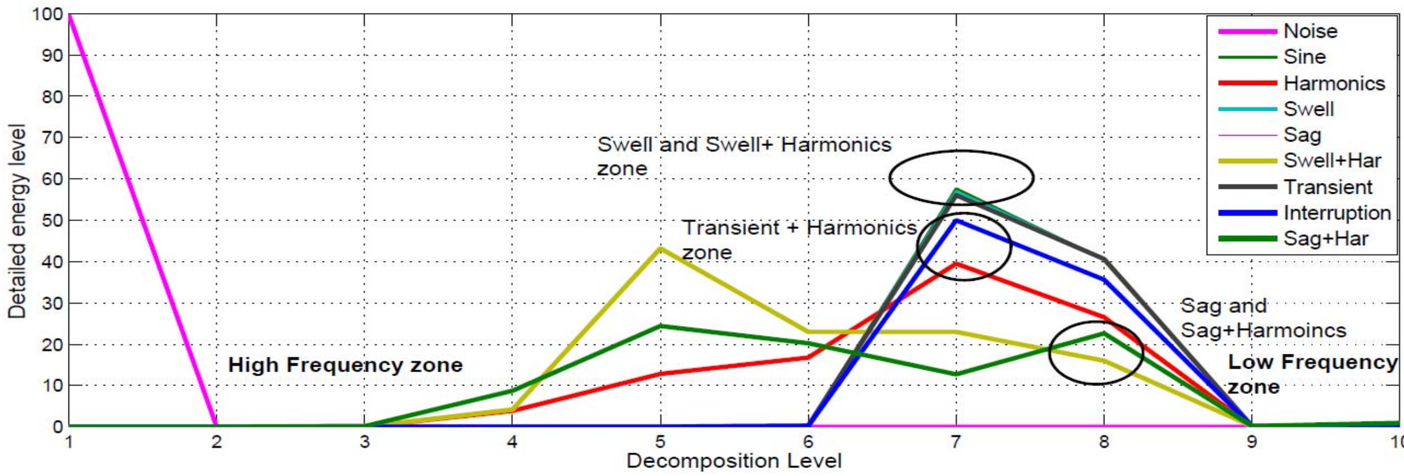

Fig. 9. MRA curve for the caparison of energy levles in sine wave and other PQ disturbances during MSD

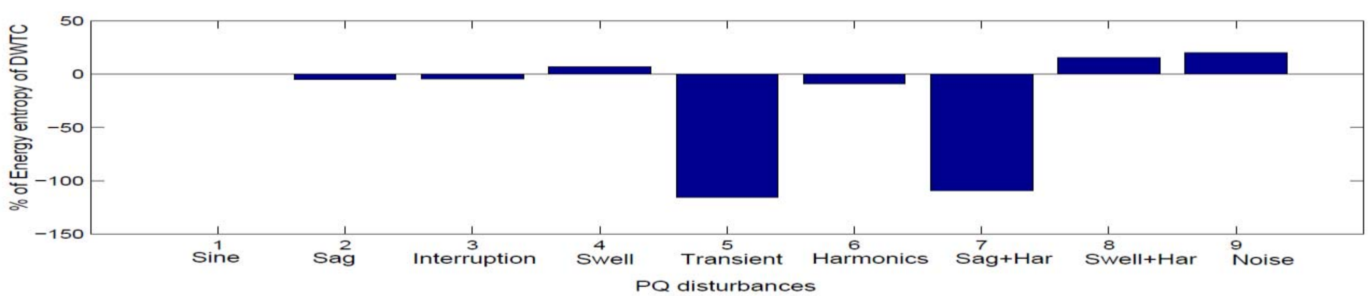

Fig. 10. Bar chart for classification of PQ events using percentage energy entropy of DWTC.

V. CONCLUSION

This paper presents, DWT-MSD based detection and classification of ten classes of all the single power quality events combined with different PQ events. All these power quality events are generated and detected using MATLAB 2014a software. PQ disturbances has energy content at each MSD level and frequency components contained in this are used as features to classify this events. The analysis and results presented in this paper, clearly indicates the lowest and highest energy content in respective frequency zone. Total nine events with the pure sine wave are taken for the analysis of proposed techniques. This feature of DWT and MSD gives appropriate frame to maintain an optimum time-frequency resolution at all levels of frequency. Further combination of intelligent techniques with DWT will lead to improve the % of classification accuracy for power quality disturbances.

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