Power Quality Detection and Classification Using S-Transform and Rule-Based Decision Tree

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***Abstract*—This paper presents a method for detection of Power Quality (PQ) disturbances using Stockwell's transform. Modeling equations are used for PQ disturbance generation using MATLAB program as per IEEE standards. Signals features are extracted from the time-frequency analysis based on Stockwell's transform. A rule-based decision tree are used to classify various PQ disturbances. It can be seen that high efficiency of classification is achieved using S-transform with rule-based decision tree. Several PQ disturbances are addressed with single and combined disturbances. Results demonstrate the accuracy and robustness of the proposed method in detection and recognition of single and combined PQ disturbances under noiseless and noisy conditions. The proposed algorithm also shows good performance in comparison with other reported studies.**

***Index Terms*—feature extraction, MATLAB program, power quality disturbance, rule-based decision tree, Stockwell transform, time frequency analysis**

I. Introduction

In recent years Power Quality (PQ) has become an important issue for both utilities and customers. The increasing use of equipment sensitive to power system disturbances and their related economic aspects forced the distribution utilities to adapt a new methods for continuously monitor the power quality of their electrical grid. Poor PQ may cause overheating of lines, inaccurate metering and reduced efficiency of appliances [1].

To monitor electrical power quality disturbances, the Short Time Fourier transform (STFT) is most often used. This transform was successfully used for analyzing stationary signals where properties of signals do not change in time. Wavelet Transform (WT) provides a good transient signal representation corresponding to a time-frequency plane. Wider windows and short windows are used at low frequencies and high frequencies, respectively. This characteristic is appropriate for real signals such as voltage sags and transient over-voltages [2].

A lot of methods for power quality disturbance monitoring have been introduced based on signal processing and artificial intelligent techniques [3]. A method based on SVM classifier and S-Trans-form for power quality disturbances classification, with accurate results has been reported in [4]. The S-transform with neural network based decision system is used to generate contours and feature vectors for pattern classifications. The result was excellent characterization of both steady state and transient PQ signals [5]. A method was presented that uses the S-transform, Time-Time transform (TT-transform), and Artificial Neural Network (ANN) for the identification and categorization of PQ disturbances with very high accuracy [6]. It was shown that the disturbance features extracted using the S-transform and an ANN, can be identified by visual inspection [7]. A comparison study for detection and classification of PQ disturbances using S-transform and CWT algorithm has been presented in [8]. PQ disturbance classification approach based on S-transform with a feature-oriented width factor and PNN has better performance in comparison with those presented in other research studies [9]. A Multi-resolution generalized ST and PSO improved DT has been presented to extract six features from the original signal with high fitness value [10]. Sparse Signal Decomposition (SSD) on over complete hybrid dictionary (OHD) matrix method achieved significantly better classification results as compared with other existing methods [11]. The Kalman filter approach was used to extract some PQ signal features to be further analyzed through fuzzy system with good classification accuracy [12]. Twelve simple and hybrid PQ disturbances in wind-grid integrated system was successfully detected and classified using fast TT-transform and learning machine with reduced computational efficiency even in noisy environment [13]. A new method has been proposed using Hilbert transform and ANN technique for detection and classification of three and nine types of disturbances respectively with high classification efficiency [14], [15]. A combined histogram based method with a Discrete Wavelet Transform (DWT) based technique was used to extract the features of the PQ disturbance in the first stage which was used as an input to an Extreme Learning Machine (ELM) for final PQ signal classification, the new method was tested in real PQ events database with accurate classification results [16].

In this paper a method using S-transform and feature extraction for detection and classification of PQ disturbances has been presented. Features of signals have been extracted from time frequency representation obtained from ST. The rule-based DT classifier which makes use of these features to classify various PQ disturbances have been proposed. The performances of

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the proposed algorithm has also been studied in the noisy environment with 20 dB SNR and efficiency comparison between the new method and other methods used in the literature has been carried out.

II. Stockwell Transform

Stockwell proposed the S-transform in 1996. As an extension to short-time Fourier transform and continuous wavelet transform. It performs multi-resolution analysis of a time varying signal while retaining the absolute phase of each frequency. It uses window whose width varies inversely with frequency, which results in high time resolution at high frequency and high frequency resolution at low frequency. The input signal is $h(t)$, which after the S-transform will become.

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) w(\tau - t, f) e^{-i2\pi ft} dt \tag{1}$$

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-t^2 f^2/2} \tag{2}$$

where $w(t, f)$ is the Gaussian window function, and $\sigma(f) = 1/|f|$ is the window width.

From (1), we can see that the S-transform is different from STFT, as the height and the width of gauss window vary with changing frequency.

The output of S-transform is a complex matrix of the size $n \times m$ called S-matrix. S-matrix (rows): represents the time-domain distribution of the signal in the particular frequency. S-Matrix (columns): represents the amplitude frequency characteristics. From the S-matrix important information in terms of magnitude, frequency and phase can be extracted of the signal in some certain time.

The main plots that can be extracted from the ST-matrix: Time-frequency contour, amplitude curve, phase curve, amplitude-frequency curve, the sum absolute values curve.

III. Proposed Methodology of PQ Event Detection

Rule-based decision tree algorithm will be used for detection, classification and localization of the PQ disturbances as shown in Fig. 1.

Signals of various PQ disturbances have been generated using MATLAB as per IEEE-1159 standard. (Voltage sag, swell, interruption, harmonics, harmonic with sag and harmonic with swell).

The PQ signals have been Analyzed using S-transform to obtain S-matrix. After that the features F1 to F6 have been extracted from time frequency representation using S-matrix.

Various disturbance signals are designated by the class symbols from S_2 to S_7 and the pure sine wave is designated by S_1. The rules for the DT is governed by the features F1 to F5, while F6 is used to localize the disturbance in time.

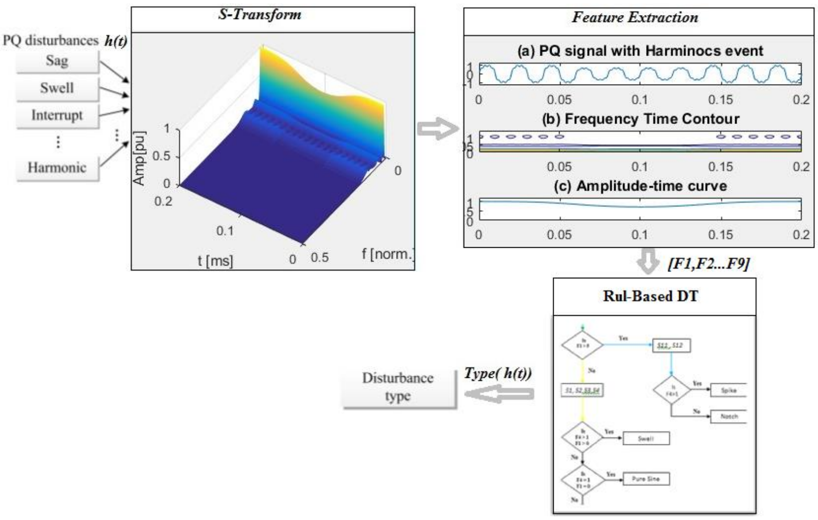

Fig. 1. PQ disturbance detection scheme using rule-based DT.

TABLE I. Mathematical Model of PQ Disturbances

S	Type	Equation	Parameters
S_1	Pure sine wave	$\sin(\omega t)$	f=50Hz, $\omega=2\pi f$
S_2	Voltage sag	$h(t)=(1-\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1\le\alpha\le0.9$, $T\le t_2-t_1\le 9T$, $t_1\le t_2$, $u(t)=1$ $(t\ge0)$, $u(t)=0$ $(t<0)$
S_3	Voltage swell	$h(t)=(1-\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1\le\alpha\le0.8$, $T\le t_2-t_1\le 9T$
S_4	Interruption	$h(t)=(1-\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.9\le\alpha\le1$, $T\le t_2-t_1\le 9T$
S_5	Harmonics	$h(t)=\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t)+\alpha_7\sin(7\omega t)$	$0.05\le\alpha3\le0.15$, $0.05\le\alpha5\le0.15$, $0.05\le\alpha7\le0.15$, $\sum\alpha i^2 = 1$
S_6	Harmonic with sag	$h(t)=(1-\alpha(u(t-t_1)-u(t-t_2)))(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t)+\alpha_7\sin(7\omega t))$	$0.1\le\alpha\le0.9$, $T\le t_2-t_1\le 9T$, $0.05\le\alpha3\le0.15$, $0.05\le\alpha5\le0.15$, $0.05\le\alpha7\le0.15$, $\sum\alpha i^2 =1$
S_7	Harmonic with swell	$h(t)=(1-\alpha(u(t-t_1)-u(t-t_2)))(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t)+\alpha_7\sin(7\omega t))$	$0.1\le\alpha\le0.8$, $T\le t_2-t_1\le 9T$, $0.05\le\alpha3\le0.15$, $0.05\le\alpha5\le0.15$, $0.05\le\alpha7\le0.15$, $\sum\alpha i^2 =1$

IV. PQ Disturbance Analysis Using S-Transform

In this part the analysis of various PQ disturbances based on the features extracted from ST will be presented. The disturbance signals have been generated based on IEEE-1159 standard using MATLAB program. Table I represents the mathematical modeling for the generated PQ signals.

All the generated signals with frequency of 50Hz, 10 cycles and sampling frequency of 3.2kHz. The disturbance signals was denoted by symbols S_2 to S_7, while the pure sine wave was denoted by S_1, these signals was analyzed by S-matrix.

The plots obtained from S-matrix include magnitude-time curve, frequency contour, phase curve, amplitude - frequency curve, sum of absolute values curve (the sum of each column of the S-matrix, and the second derivative of the sum of absolute values curve which is used to localize some types of disturbances in time such as (voltage swell, sag and interruption).

A. Pure Sine Wave

The plots obtained for the pure sine wave is considered as a reference for PQ disturbance detection. All curves were of constant amplitude except for amplitude-frequency curve which showed one amplitude appeared at 50Hz.

B. Voltage Sag

Voltage sag of (30%) and related ST plots are shown in Fig. 2. The voltage sag can be recognized from the change in the amplitude of various curves such as, frequency contour, amplitude–time curve, and sum of absolute values curve Fig. 2 (b), (c), and (d), respectively. From Fig. 2 (e) which is the second derivative of the sum of absolute values curve we can easily localize the time of the disturbance between (0.06s – 0.14s).

C. Voltage Swell

Voltage swell of (30%) and related ST plots are shown in Fig. 3. The voltage swell can be recognized from the change in the amplitude of various curves such as, frequency contour, amplitude –time curve, and sum of absolute values curve Fig. 3 (b), (c), and (d), respectively. From Fig. 3 (e) which is the second derivative of the sum of absolute values curve we can easily localize the time of the disturbance between (0.06s – 0.14s).

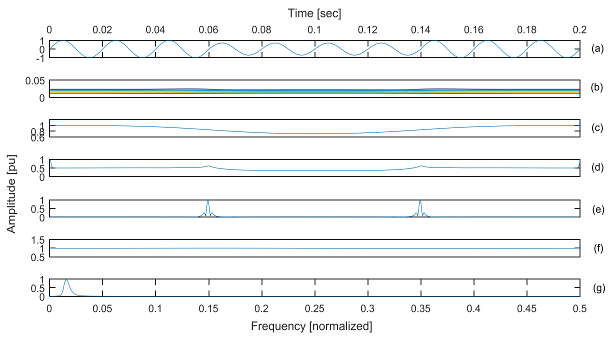

Fig. 2. Voltage sag of (30%) and related ST: (a) Voltage sag, (b) frequency contour, (c) amplitude-time curve, (d) sum absolute values curve, (e) second derivative of sum absolute values curve, (f) phase curve, and (g) amplitude-frequency curve.

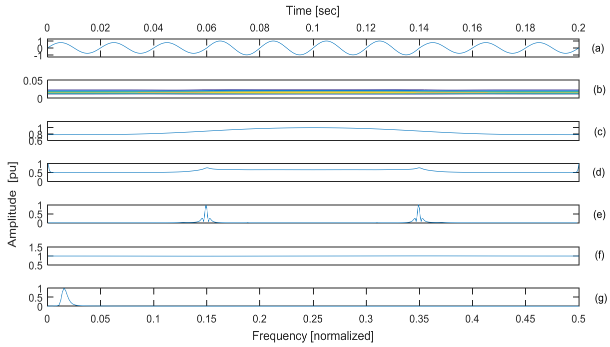

Fig. 3. Voltage swell of (30%) and related ST: (a) Voltage swell, (b) frequency contour, (c) amplitude-time curve, (d) sum absolute values curve, (e) second derivative of sum absolute values curve, (f) phase curve, and (g) amplitude-frequency curve.

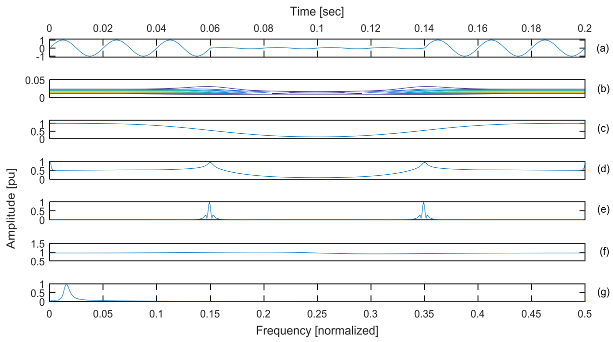

Fig. 4. Voltage interruption of (8%) and related ST: (a) Voltage interruption, (b) frequency contour, (c) amplitude-time curve, (d) sum absolute values curve, (e) second derivative of sum absolute values curve, (f) phase curve, and (g) amplitude-frequency curve.

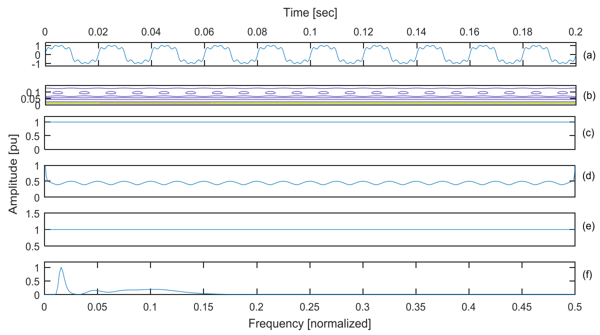

Fig. 5. Harmonic and related ST: (a) Harmonic, (b) frequency contour, (c) amplitude-time curve, (d) sum absolute values curve, (e) phase curve, and (f) amplitude-frequency curve.

D. Voltage Interruption

Voltage Interruption of (8%) and related ST plots are shown in Fig. 4. The voltage interruption can be recognized from the change in the amplitude of various curves such as, frequency contour, amplitude –time curve, and sum of absolute values curve Fig. 4 (b), (c), and (d), respectively. Also some discontinuities in the frequency contour curve can be noticed. From Fig. 4 (e) which is the second derivative of the sum of absolute values curve we can easily localize the time of the disturbance between (0.06s – 0.14s).

E. Harmonic

Harmonic and related ST plots are shown in Fig 5. It can be depicted from continuous ripples in frequency contour plot and sum of absolute values curve Fig. 5 (b) and (d), respectively. A finite value of frequency between the normalized frequencies 0.05 to 0.15 is another indication of the presence of harmonics.

F. Harmonic with Sag

Harmonic with sag and related ST plots are shown in Fig. 6. It can be depicted from continuous and discontinuous ripples in frequency contour plot Fig. 6 (b) and continuous ripples in the sum of absolute values curve Fig. 6 (d). A decrease in the amplitude-time curve and sum of absolute values curve when combined with a finite value of frequency between the normalized frequencies 0.05 to 0.15 gives an indication of the presence of harmonics with sag.

G. Harmonic with Swell

Harmonic with swell and related ST plots are shown in Fig. 7. It can be depicted from ripples in frequency contour plot Fig. 7, (b) and continuous ripples in the sum of absolute values curve Fig. 7, (d). An increase in the amplitude-time curve and sum of absolute values curve when combined with a finite value of frequency between the normalized frequencies 0.05 to 0.15 gives an indication of the presence of harmonics with swell.

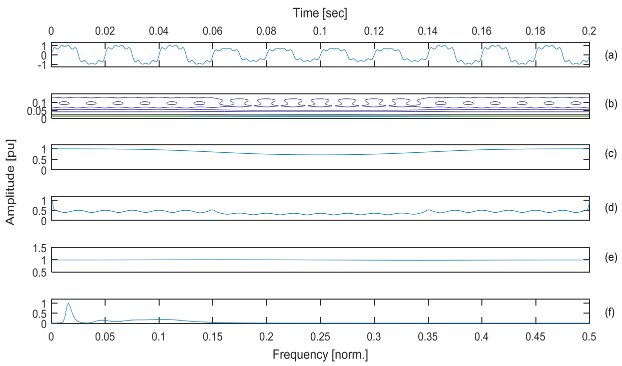

Fig. 6. Harmonic with sag and related ST: (a) Harmonic with sag, (b) frequency contour, (c) amplitude-time curve, (d) sum absolute values curve, (e) phase curve, and (f) amplitude-frequency curve.

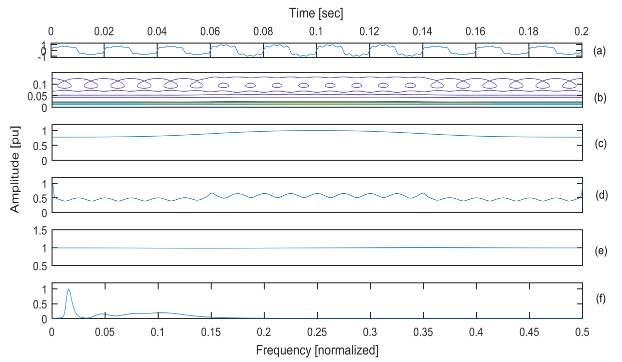

Fig. 7. Harmonic with swell and related ST: (a) Harmonic with swell, (b) frequency contour, (c) amplitude-time curve, (d) sum absolute values curve, (e) phase curve, and (f) amplitude-frequency curve.

V. S-Transform Feature Extraction

The statistical features extracted from the ST plots of power quality disturbances are labelled as F1, F2, ⋯ F6. The definitions of these features are as follows.

F_1: Sum factor (S_f):

$$S_f = \max(S) + \min(S) - \max(R) - \min(R)$$

where S and R are the arrays of data of the sum of absolute values of the signal with PQ disturbance and pure sine wave (reference) respectively.

F_2: Number of peaks in the frequency amplitude curve.

F_3: Skewness of phase curve. Skewness of a signal is given by the relation:

$$S = \frac{E(x-\mu)^3}{\sigma^3} \tag{3}$$

where x is the array of data of signal, μ is the mean of x, σ is the standard deviation of x, and E is the expected value of the quantity.

F_4: Amplitude factor:

$$A_f = (1 + (C - A) + (D - B))$$

where C and D are respectively the maximum and minimum value of amplitude curve of arbitrary signal. A and B are respectively the maximum and minimum values of amplitude curve of reference signal.

F_5: Kurtosis of amplitude-frequency curve. The Kurtosis of a signal is defined as:

$$k = \frac{E(x-\mu)^4}{\sigma^4} \tag{4}$$

where x is the array of data of signal, μ is the mean of x, σ is the standard deviation of x, and E is the expected value of the quantity.

F_6: Second order derivative of sum absolute values curve:

$$F_6 = \frac{\partial^2 f}{\partial n^2} = f(n+1) + f(n-1) - 2f(n) \tag{5}$$

where $f(n)$ is the sum of absolute values of the signal and n is the sample number. The sharp peaks detected in the feature F_6 helps to localize the PQ events such as voltage sag, swell, interruption and oscillatory transient.

Table II. S-Transform Based Features of PQ Disturbances

PQ Disturbance	PQ Symbol	Features of PQ Disturbances				
		F_1	F_2	F_3	F_4	F5
Pure sine wave	S1	0	1	-1.3514	1	74.03
Voltage sag	S2	-0.0133	1	3.66E-13	0.6763	57.5538
Voltage swell	S3	0.3675	1	-6.63E-14	1.2234	71.2947
Interruption	S4	0.8248	1	8.42E-14	0.1162	59.9162
Harmonics	S5	2.1387	2	-1.5137	0.9641	57.2682
Harmonic with sag	S6	1.982	2	3.66E-13	0.6763	57.5538
Harmonic with swell	S7	4.8407	2	-4.30E-13	1.1681	39.505

VI. Detection and Classification Using Rule-Based Decision Tree

The rule based decision tree is used to classify the PQ disturbances. This algorithm is based on the features F_1 to F5 to build the rules for classification. Zero value of F_1 indicates no disturbance whereas finite value indicates a disturbance in the signal. Numerical values of the features (F_1 to F_5) used for the decision rules are presented in Table II. First signals are classified into two main groups using the number of peaks in the amplitude frequency curve (F_2). One group with one peak (F_2=1) whereas the data of the other group belongs to more than one peak. The signals classified under the one peak group are further classified into subgroups based on F_1. The process continues till final disturbance type classification.

The proposed algorithm is illustrated in Fig. 8 using a flowchart. Threshold values have been obtained based on multi-resolution analysis of S-transform on hundreds of the signals generated in each category by varying the parameters mentioned in Table I. Efficiency of proposed algorithm with and without noise has been done based on the testing of all types of PQ disturbances (S_1, S_2, ⋯ S_7) using hundred data sets of each disturbance and provided in Table III.

TABLE III. RULE-BASED DECISION TREE CLASSIFICATION RESULT

PQ event	PQ symbol	Correctly Classified		Efficiency (%)	
		Without noise	20 dB SNR	Without noise	20 dB SNR
Pure sine wave	S1	100	100	100%	100%
Voltage sag	S2	100	98	100%	98%
Voltage swell	S3	100	100	100%	100%
Interruption	S4	99	97	99%	97%
Harmonics	S5	98	97	98%	97%
Harmonic with sag	S6	99	98	99%	98%
Harmonic with swell	S7	100	97	100%	97%
Overall Efficiency				99.4%	98.1%

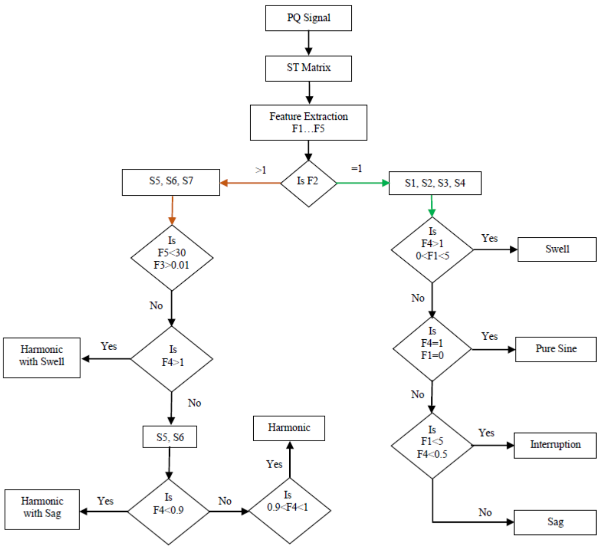

Fig. 8. Block diagram for classification of power quality disturbance.

VII. PERFORMANCE COMPARISON

Power quality disturbances classification accuracy of the proposed algorithm was compared with the methods proposed in the references [1], [3], [5], [6], [11], [13] and [14]. These articles have been selected due to the fact that each article represents a method which is different than the other methods. Table IV compares the performance of various algorithms with and without noise, the efficiency comparison has been done on the basis of identical disturbances types between the proposed and other algorithms. From Table IV it is evident that higher efficiency is achieved using the proposed algorithm in comparison with the algorithms proposed in the references [1], [3], [5], [6]], [11] and [14], except for the method proposed in reference [13] where it has better classification accuracy in noiseless environment however in noisy environment the proposed algorithm has better classification efficiency.

TABLE IV. PERFORMANCE COMPARISON

Reference	Type of algorithm	No. of compared PQ disturbances	Overall efficiency (%)	
			without noise	20 dB SNR
[1]	(DWT+WN)	6	98.5	98.2
[3]	(ST+SVM)	5	91.1	-
[5]	(ST+NN)	5	97.7	-
[6]	(ST+TT+ANN)	4	92.1	-
[11]	(SSD+HD)	7	96.7	95.4
[13]	(FTT+ELM)	7	99.56	95.38
[14]	(HT+ANN)	3	98.6	-
Proposed	(ST+DT)		99.14	98.20

VIII. CONCLUSION

The detection and classification of the PQ disturbances have been effectively done with the aid of features F1 to F5 extracted from the S-transform. The feature F6 is proposed to localize the various PQ disturbances in time. The performance of the proposed algorithm has been tested using 100 data sets of each type of disturbance to establish the effectiveness. The proposed algorithm proved to have an efficiency greater than 98% even in noisy environment. Thus, ruled based decision tree technique using features based on S-transform can be effectively utilized to detect and classify various PQ disturbances.

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