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ABSTRACT

To improve power quality (PQ), detecting the particular type of disturbance is the foremost thing before mitigation. So monitoring is needed to detect the PQ disturbance that occurs in a short duration of time. Classification of real-time PQ disturbances under noisy environment is investigated in this method by selecting an appropriate signal processing tool called fusion of time domain descriptors (FTDD) at the feature extraction stage. It's a method of extracting power spectrum characteristics of various PQ disturbances. Few advantages like algorithmic simplicity and local time-based unique features makes the FTDD algorithm ahead of other techniques. PQ events like voltage sag, voltage swell, interruption, healthy, transient and harmonics mixed with different noise conditions are analysed. multiclass support vector machine and Naïves Bayes (NB) classifiers are applied to analyse the performance of the proposed method. As a result, NB classifier performs better in noiseless signal with 99.66%, wherein noise added signals both NB and SVM are showing better accuracy at different signal to noise ratios. Finally, Arduino controller-based hardware tool involved in the acquisition of real-time signals shows how our proposed system is applicable for industries that make detection simple.

1. Introduction

According to the Electrical power research Institute (EPRI) survey $15 billion to $24 billion is losing in U.S. economy due to PQ disturbances [1]. Power quality (PQ) is becoming an important issue nowadays in domestic and industrial fields [2]. Even in small industries too we are using personal computers, servers and UPS. Moreover, equipments like power electronic devices, adjustable speed drives, microprocessors, logic controllers, switched mode power supplies and Energy efficient lightings are causing distortions in the utility side. The above-mentioned causes may affect memory loss in computers, error in electronic circuits and malfunction of controllers. Hence monitoring of PQ and automatic detection of disturbance is much essential [3]. The magnitudes and time limits of voltage and current signals are enlisted in IEEE standard 1159-2009 [4]. Among the number of signal processing techniques used in feature extraction of PQ disturbances Fourier transform (FT) is one of the fastest technique, but it is not suitable for non-stationary signals. The next implementation of FT is the fast Fourier transform (FFT) in which the performance is poor if signal changes suddenly similar to transients [5]. Later short time Fourier transform (STFT) is used, it gives both time and

frequency information, but due to constant window size it covers only a portion of the signal [6].

The above requirements are fulfilled by the most popular Wavelet Transform (WT) [7], using short window size for high frequency and long window size for low frequency is the method adopted here. Still few drawbacks exist in wavelet transform such as (i) Performance depends on choosing the mother wavelets tools like daubechies (db) symlets, coiflets, harr etc. Mostly db4, db6 are suitable for fast changing signals and db8 are suitable for slow changing signals. (ii) Performance is degraded under noisy conditions.(iii) Its inability to estimate the Fourier frequencies and it has a local phase reference. These drawbacks of WT are overcome by introducing Stockwell Transform (ST) [8,9], It provides better feature extraction and characterization. Unlike wavelet transform it maintains an accurate reference phase also. Besides heavy computational burden slow down the runtime if sample rate is high. Other approaches like Kalman Filter is preferred for its noise tolerance capability [10]. Still it fully depends on the filter model, if signal mismatches the filter model it leads to error. Due to advancement in signal analysis Hilbert–Huang transform was proposed in [11] along with empirical-mode

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decomposition. A time-frequency analysis method of analysing PQ disturbances using Gabor–Wigner transform is presented in [12], but classification stage is not proceeded. Ganyun et al. [13] recently proposed a semi-supervised method of classifying PQ disturbances without known training data. A sparse signal decomposition technique is applied in [14], detailed and approximation signals are considered as features for detection and Decision tree method for classification. Moreover in [15], real-time detection of disturbances under various noise levels based on time –frequency-scale transform is performed and analysis is made by comparing three different classifiers. Furthermore, Discrete Gabor Transform-based feature extraction and Type 2 fuzzy kernel (T2FK)-based SVM is proposed in [16] around nine types of PQ events are classified. Recently Stockwell Transform emerges in recognizing PQ disturbances along with KNN and rule-based decision tree in [17]. In addition, few literatures highlights the feature selection stage aiming to reduce the size of large extracted feature in turn minimize the computational burden also to increase the performance. Still around 25 feature extractors are proposed in various literatures we need an extraction technique which provides unique features, because in PQ signals we can find only slight variations between one another.

This paper presents a fusion of time domain descriptors (FTDD)-based technique to discriminate the PQ disturbances from normal pure sinusoidal signal. FTDD provides informative features derived from first and second derivative leads to better classification. Already FTDD features are applied for myoelectric signals from EMG and ECG devices, also it proven better pattern recognition for EMG signals when compared with other 50 feature extraction techniques. Actually, myoelectric signals stimulated from our human body are very low signals in the range of milli or micro volts. In such signals the variations between normal and abnormal patients are very mild. The proposed FTDD method shows a high resolution and capability in extracting features in negligible distortions. This initiates the researcher to utilize this technique in detection of PQ disturbances application. In PQ, few disturbances are almost identical but only the magnitude and frequency changes slightly. In order to detect such distortions we are using power spectrum and graphical indices like Sparseness (S), Waveform length ratio (W_L) and Irregularity factor (I_F). The comparative studies and analysis shows the robustness of the proposed system. This method is implemented for real-time signals acquired using Arduino controller interfaced with computer. Samples of PQ disturbances like sag, swell, harmonics, transients and interruptions are captured at various load conditions. This signals are mixed with noises at 20, 30, 40, 50 and 60 db signal to noise levels using synthetic noise generator. Thus FTDD algorithm is proven to be the best for noise mixed signals and

when it is merged with Naives Bayes (NB) and multi SVM classifiers better accuracy is achieved. While comparing the performance with the other Naïve Bayes classifier, it is found that NB is more effective than multi-SVM under noise added signals.

The paper is organized in five sections: Section 2 describes the proposed methodology, FTDD-based Feature extraction with algorithm is presented in Section 3. Section 4 explains the working of classification methods. The results and performance analysis are discussed in Section 5 and concluded in Section 6.

2. Proposed methodology

The flow diagram of the proposed method is shown in Figure 1. According to the proposed method shown in flow diagram an Arduino-based PQ analyser is used to collect PQ samples from various loads like induction motors, switched mode power supplies, servers, UPS, capacitor banks, choke and other industrial appliances. The collected PQ samples are reconstructed into waveform distortions and this signals are further processed to extract features. Before extracting the features, noises are added at various db levels to validate our system is effective under noisy conditions too.

FTDD is a new feature extraction tool and this approach is new in PQ area. The idea behind FTDD can be expressed in three steps (i) Nonlinearity in the time domain signal $x[k]$ is expressed as a function of frequency $x^*[k]$ using discrete Fourier transform (DFT). (ii) Compute the power spectrum $p[k]$ for the current and previous moments (iii) Using fusion technique correlate the two features obtained from current and previous windows. These extracted six features of each PQ disturbances signal are taken to multi SVM and Naïve Bayes classifier for classification The size of the feature set is minimum that reduces the computation burden and time, Also this system can able to detect both noisy and noiseless signals which provides a best solution for different applications.

2.1. Acquisition of real-time signal

Few single phase loads connected to a 230 V, 50 Hz supply is measured with a hardware setup that can be used as an analyser to acquire the real-time signals. It constitutes of arduino microcontroller, potential divider, clamper circuit, interfacing cards and multimeter. This arrangement is interfaced with personal computer to acquire five categories of PQ events like voltage sag, voltage swell, harmonics, interruption and transients, along with the pure signal. The hardware setup is tested in electrical machines like induction motors, residential appliances like UPS, computers, SMPS and across capacitor banks in institutional laboratories. The values are converted to per units and stored in the database. The numerical data are reconstructed into wave shapes
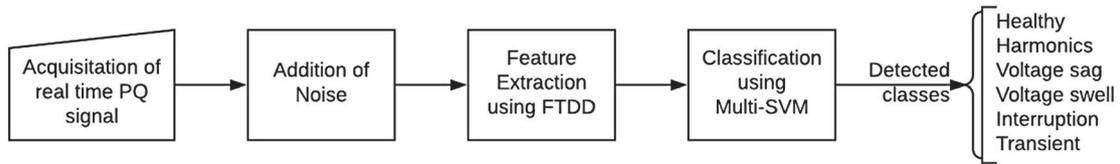
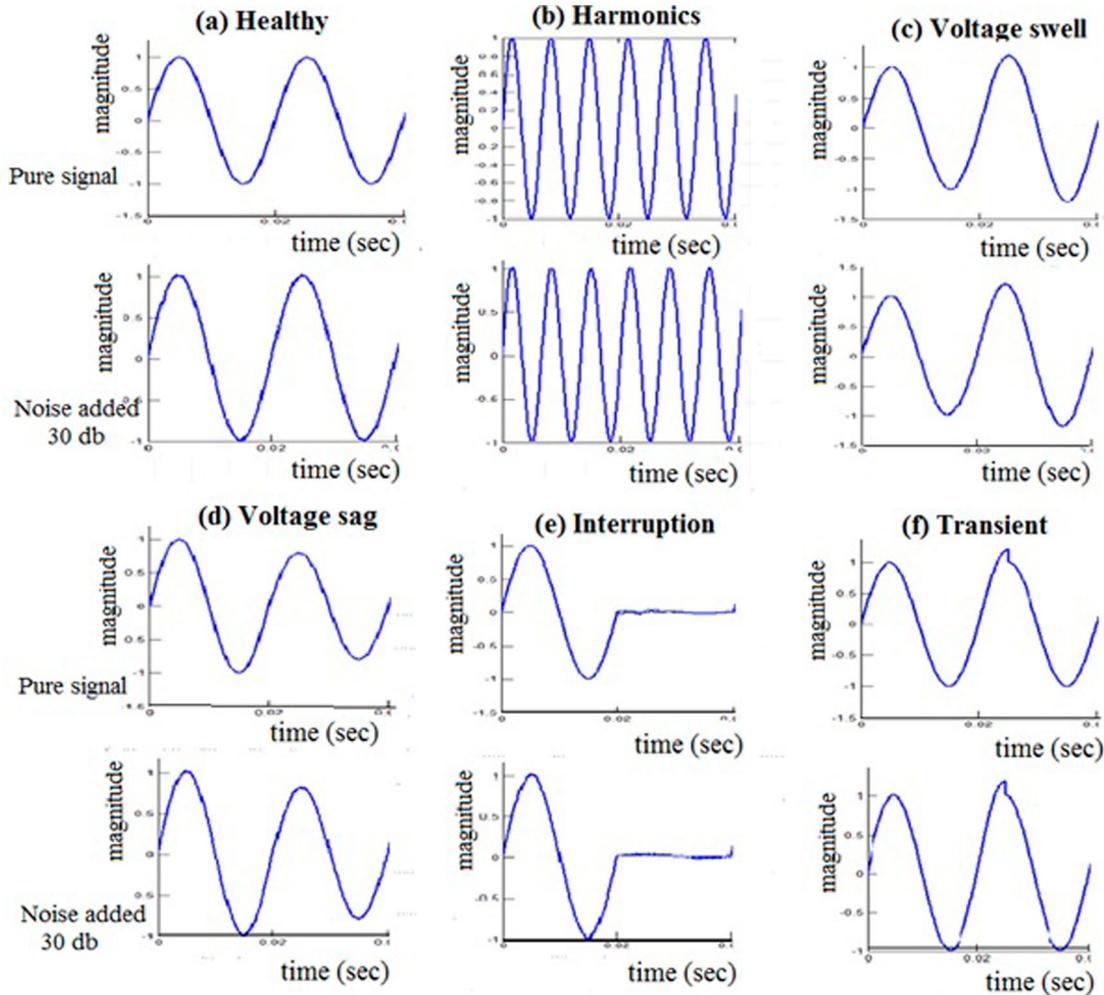**Figure 1.** Flow diagram of proposed method.

Figure 2. Samples of pure and noise added PQ disturbances.

and noises are added with the signal using MATLAB in different signal to noise ratio (SNR). The dataset consist of 200 samples of all classes, we have considered only 10 cycles for processing. For convenience a set of samples with pure and 30 db noise added signals for two cycles are shown in Figure 2.
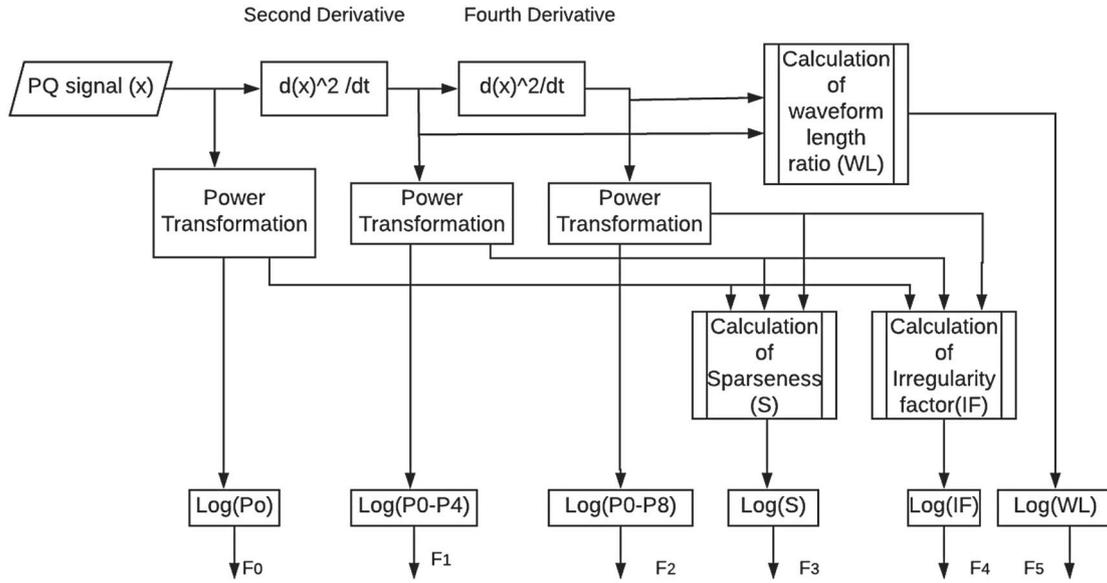
3. Feature extraction using FTDD

The original distorted signal is processed to change time domain signal to a new signal from which few relevant information's are extracted called features which is more essential for classification. The extraction of better feature is the major area in the performance of classifier. If we minimize the size of the feature data the classifier can able to recognize the signal easily and correctly, thereby the efficiency of classifier is increased.

The method of extracting features using FTDD [18] is shown in Figure 3. It starts with the input signal $x[j]$ of length $N = 2000$ at sampling frequency 10 KHz. FTDD algorithm basically starts from the Parseval's theorem which states that the sum of square of the function is equal to the sum of square of its transform. The disturbance signal in time domain $x[k]$ is transformed as a function of frequency $x^*[k]$ using DFT.

$$\sum_{j=0}^{N-1} [x(j)]^2 = \frac{1}{N} \sum_{k=0}^{N} [x(k)x^*(k)] = \sum_{k=0}^{N-1} p(k). \quad (1)$$

Here, 'k' is the frequency index, $p(k)$ is the power spectrum obtained by multiplying $x[k]$ by its conjugate and divided by N. Thus the square root of zero-order derivatives indicating the power spectrum in frequency

Figure 3. Process of feature extraction using FTDD.

domain is chosen as the zero-order moment 'm_0' [19]

$$m_0 = \sqrt{\sum_{j=0}^{N-1} x(j)^2}. \qquad (2)$$

Similarly, the square root of first derivative indicating the power spectrum corresponding to frequency $kx[k]$ denotes second-order moment 'm_4'

$$m_4 = \sqrt{\sum_{j=0}^{N-1} k^2 p(k)}. \qquad (3)$$

Repeating the same procedure by taking the second derivative again gives the fourth- and eighth-order moments 'm_4'and 'm_8' shown in (4). Further increasing the higher derivatives of the signal reduces the energy of the signal. Power transformation is done in order to normalize and reduce the effect of noise present in features

$$m_8 = \sqrt{\sum_{j=0}^{N-1} k^4 p(k)}. \qquad (4)$$

After normalization first three features are extracted from the moments

$$\left.\begin{array}{l} f_1 = \log(m_0) \\ f_2 = \log(m_0 - m_4) \\ f_3 = \log(m_0 - m_8) \end{array}\right\}. \qquad (5)$$

The other three features can be calculated from zero-, fourth- and eighth-order moments using Equations (6)–(8). The factors like Sparseness, Irregularity factor and Waveform length ratio are used to differentiate the nature of waveform from normal sine wave. Sparseness (S) is the feature that gives the measure of energy that is packed in a vector. If all the elements are

same it gives a sparseness level equal to zero, otherwise the value is greater than zero.

$$f_4 = \log\left(\frac{m_0}{\sqrt{m_0 - m_4}\ \sqrt{m_0 - m_8}}\right). \qquad (6)$$

Irregularity Factor (I_F) defines the ratio of number of upward zero crossings and number of peaks. Irregularity factor can be either computed directly from the signal using Number of Zero crossings (NZ) and Number of Peaks (NP) or using the spectral moments [20].

$$f_5 = \log\left(\frac{(NZ)}{(NP)}\right) = \log\left(\frac{\sqrt{m_4/m_0}}{\sqrt{m_8/m_4}}\right). \qquad (7)$$

Waveform length ratio (W_L) is defined as the ratio of waveform length of first derivative to the waveform length of second derivative

$$f_6 = \log\left(\frac{\sum_{j=0}^{N-1} |\Delta^2 x|}{\sum_{j=0}^{N-1} |\Delta^4 x|}\right). \qquad (8)$$

The signal input $x(j)$, number of steps away from current window (20), size of window (2000) and spacing between the windows (0.05) are the required inputs to the algorithm. According to FTDD-based feature extraction process in Figure 3, the proposed six features are initially extracted and set of features per signal are recorded. At the final stage the features of current window and previous window are multiplied and this process is called FTDD. In such a way we can correlate with the 2nd, 3rd or 4th previous window, and then choose the nth window with improved accuracy. Features thus obtained are having uniqueness and more variation for slight changes in the input signal. A set of features extracted by FTDD are tabulated in Table 1.

Table 1. Extracted feature set using FTDD for a set of classes.

Classes	f1	f2	f3	f4	f5	f6
Healthy (C1)	0.9684	0.9612	0.7853	0.2605	0.4823	0.5706
Harmonics (C2)	0.9293	0.9999	0.9029	0.3724	0.7221	0.4169
Sag (C3)	0.9673	0.9632	0.7921	0.2679	0.4786	0.7562
Swell (C4)	0.9694	0.9594	0.7825	0.2604	0.4774	0.7087
Interrupt (C5)	0.9418	0.9848	0.9974	0.6068	0.7804	0.9045
Transient (C6)	0.9688	0.9909	0.8955	0.5618	0.6351	0.8389

4. Classification stage

4.1. NB classifier

NB algorithm is a powerful tool in performing the classification task by using Bayes Probability method [21]. In NB classifier both statistical and supervised learning methods are followed. In this method, it consider all the features and properties of any sample to find the probability. This method is well known in predicting multiclass variables, the fold value is chosen as 0.5 for splitting test data and train data. The methodology adopted for classifying PQ signals using NB is enumerated in the algorithm below.

Algorithm of Naïve Bayes classifier

Step 1: Read the data.
Step 2: Create a partition object using the fold value.
Step 3: Create a training and test set.
Step 4: Calculate the conditional probability using the Bayesian probability equation (9).

$$P(C_k/x) = \frac{P(C_K)P(x/C_k)}{P(x)}, \quad (9)$$

where $P(C_k)$ is the prior probability; $P(x/C_k)$ the likelihood; $P(x)$ the predictor prior probability; $P(C_k/x)$ the posterior probability.

Step 5: Compute normal distribution and kernel distribution
Step 6: Get the probability of test set from the training
Step 7: Compare the actual output with the predicted output else,
Step 8: Maximize $P(C_k/(x_i \ldots \ldots x_n))$ to get predicted output of test set.

4.2. Support vector machine

SVM is a powerful method for solving pattern classification problems [22]. SVM algorithm is based on supervised learning theory introduced by Vapnik [23]. In this method, a model is built using the training samples and by this model it can recognize the class of any new sample. The aim of SVM model is to choose a hyper plane that can able to separate the two classes. If there are only two classes it is a binary SVM classifier, in our data set there are different classes with nonlinearity nature so we find it difficult to separate. Hence nonlinear SVM is adopted using a technique of Kernel function; here the input vector is mapped in a higher dimensional feature space $\mathcal{H}$.

The hyper planes are denoted as $\vec{w} \cdot x - b = 1$ and $\vec{w} \cdot x - b = -1$

In order to maximize the distance between the hyper plane and the data points we have to minimize $|\vec{w}|$

$$\min|\vec{w}| \text{ Subject to } y_i(\vec{w} \cdot x - b) \geq 1, \quad (10)$$

where, $|\vec{w}|$ is the normal vector to the hyper plane, 'x_i', 'y_i' denote the feature and classes. Let x_i is the input vector belongs to any one class $y \, \varepsilon \, \{-1, 1\}$. Using the nonlinear transformation $\varphi(x)$ mapping is done through suitable basis function. Also it uses the linear model in feature space called the kernel function. Basically, SVM separates only binary classes ($k = 2$), but practically we have to discriminate more than two classes. In our system, multiclass SVM can be decomposed into a series of binary problems [16].

$$\text{Min} \frac{1}{N} \sum_{i=1}^{N} \max(0, 1 - y_i(|\vec{w}|x_1 - b)) + \lambda|\vec{w}|^2, \quad (11)$$

$$\varphi = (0, 1 - y_i(\vec{w} \cdot x_1 - b)), \quad (12)$$

where φ is the primal factor. Initially in multi-SVM, the training data and training labels of each class are given as input. dendrogram-based training is done and clusters are formed, then SVM is implemented at each node. The advantages like better generalization property and ability to handle large classification problems highlights SVM over conventional classifiers.

5. Results and discussion

5.1. Data acquisition using Arduino-based PQ analyser

In order to collect the PQ samples across different loads causing the distortions, a hardware-based PQ analyser is designed in cheaper cost when compared to the recent PQ analysers available in the market which is of high cost. Samples with six classes of disturbances are collected and further stored at our computer. We are able to get only six types of disturbances in our institutional premises, machines laboratory, across capacitor banks and UPS battery. This Arduino-based low cost PQ analyser is useful for industries operating under single phase loads. Furthermore, our robust classifier can able to detect if any distortions existing in the voltage signal.

5.2. Classification success of FTDD features

The dataset obtained using PQ analyser consists of totally 200 samples. When it is mixed with Gussian noise distortions at six levels from 20 to 60 db at an interval of 10 db, totally 1000 samples were obtained. Among the 1000 samples, 500 are taken for training and 500 samples for testing. The target is denoted as

(C1, C2, C3, C4, C5, C6) for the six classes. While collecting real-time signals, we may or may not get noise distorted signals. Therefore to perform a uniform analysis in all type of signals, the noise is added. Equation (13) represents how SNR is calculated. Few other feature extractors find it difficult to detect the disturbance under noisy environment. But the capability of FTDD is quite superior in detecting PQ events with noise content. Thus when 500 samples are tested, the system shows a better accuracy for different classifiers consistently. A sample feature set of each class is shown in Table 1. Only six features per sample reduce the dimension of feature size also reduces the memory space. Thereby the computation time is also reduced.

$$ \text{SNR} = 10 \log_{10} \left(\frac{P_s}{P_n} \right). \tag{13} $$

Table 2. Classification results using FTDD and SVM.

		Classification accuracy (%)				
			Noise added			
Classes	Noiseless	20 db	30 db	40 db	50 db	60 db
C1	100	100	100	100	100	94.67
C2	96.67	100	99.33	100	99.33	100
C3	98.67	96.0	90.67	98.67	96.6	96.0
C4	99.33	98.0	100	100	96.0	95.33
C5	100	98.67	98.67	98.60	98.67	96.0
C6	100	99.33	98.0	97.33	100	98.67
Overall	99.11	98.66	97.65	99.10	98.43	96.77

Table 3. Classification results using FTDD and NB.

		Classification accuracy (%)				
			Noise added			
Classes	Noiseless	20 db	30 db	40 db	50 db	60 db
C1	100	98.0	100	100	100	94.0
C2	100	100	100	99.3	99.3	100
C3	99.33	100	98.67	100	96.67	90.67
C4	98.67	98.0	100	100	96.0	95.33
C5	100	100	98.67	98.67	98.67	98.0
C6	100	99.33	97.33	98.67	100	92.67

### 5.3. Performance of SVM and NB under different noise conditions

In the classification stage, two efficient classifiers are applied to find the suitable classifier for different noisy environments. The extracted features grouped as testing and training data is further given to both SVM and Naive Bayes classifiers to analyse the performance of our proposed work. Some classifiers may show better accuracy only up to a particular noise level, but the two classifiers are superior in discriminating the disturbances. The confusion matrix of SVM classifier shows an accuracy of 99.11%, similarly Naive Bayes classifier is showing 99.66% accuracy for pure signals. The result shows only a slight decline in the classification rate in noisy conditions. A comparative analysis is done with few existing methodologies to validate our proposed system and to focus which combination pair of feature extractor and classifier is giving better accuracy. Table 2 shows the classification results with the combination of FTDD with multi-SVM. Similarly, in Table 3, the obtained accuracy with FTDD and NB is tabulated.

5.4. Performance comparison

Though a lot of literature related to the classification of PQ disturbances is available, only the references related to our work are alone taken for analysis. A survey is undergone with references where simulations are carried out in practical data with noise and noiseless signal. Here it is proved to be reliable for both noisy and noiseless signals. Tables 4–6 show the comparison separately for 20, 30 and 40 db. In most of the literature they have analysed only up to 40 db, but we have executed up to 60 db. In all cases, the accuracy of our system is ahead of existing techniques. Figure 4 shows the accuracy plot obtained through SVM and Naïve Bayes classifier. In such classification problems, NB is superior over SVM when it is combined with FTDD the performance is higher and reaches an average of 99%. Tables 2 and

Table 4. Comparative analysis of proposed system with existing methods under 20 db noise.

References	Method	Whether real data used	No of disturbances	Accuracy (%) noiseless	Accuracy (%) with 20 db
Uyar et al. [7]	WT + WNN	No	9	95.71	89.92
Eristi et al. [24]	WT + SVM	Yes	8	98.88	97.75
Abdelazeem et al. [10]	Kalman + fuzzy	Yes	7	–	92.28
He et al. [8]	HM + DT	Yes	11	–	94.36
Biswal and Dash [25]	Fast ST + DT	Yes	13	–	96.90
Valtierra-Rodriguez et al. [26]	Adaline + FFNN	Yes	12	97.75	90.53
Proposed	FTDD + NB	Yes	6	99.66	99.22

Table 5. Comparative analysis of proposed system with existing methods under 30 db noise.

References	Method	Whether real data used	No of disturbances	Accuracy (%) with 30 db
Sabarimalai et al. [14]	SSD + DT	Yes	7	99.06
Abdelazeem et al. [10]	Kalman + fuzzy	Yes	7	97.0
He et al. [8]	HM + DT	Yes	11	97.91
Eristi et al. [24]	WT + SVM	Yes	8	98.14
Moravej [27]	DWT + SVM	No	11	97.0
Proposed	FTDD + NB	Yes	6	99.11

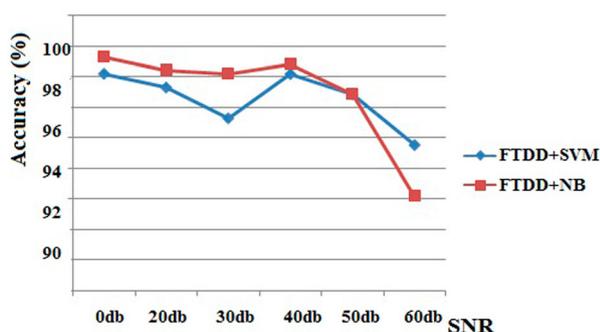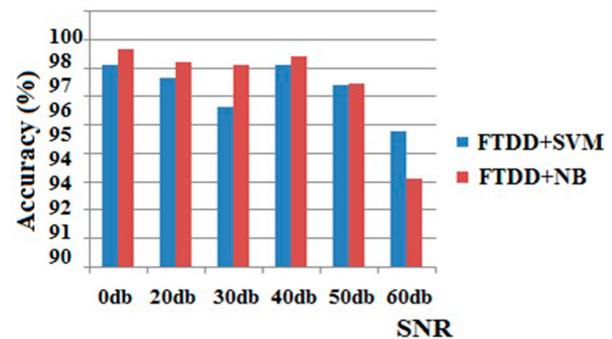**Table 6.** Comparative analysis of proposed system with existing methods under 40 db noise.

References	Method	Whether real data used	No of disturbances	Accuracy (%) With 40 db
Uyar et al. [7]	ST + NN	No	7	93.64
He et al. [8]	HM + DT	Yes	11	99.27
Abdelazeem et al. [10]	Kalman + fuzzy	Yes	7	98.71
Biswal and Dash [25]	Fast ST + DT	Yes	13	98.8
Proposed	FTDD + NB	Yes	6	99.44
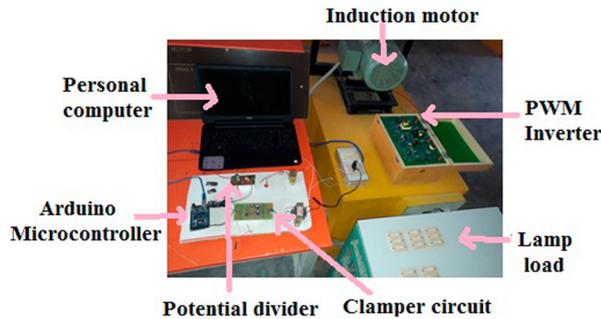
Figure 4. PQ analyser using Arduino.

Figure 6. Performance measures of SVM and NB classifiers.

3 reveals except 20 and 60 db Naive Bayes classifier is better and for SNR of 20 and 60 db SVM is performing higher. Few methods have shown higher classification rate than our proposed method because results are based on the size of the data taken from the tested samples and depends on the number of classes. Also in few literatures the algorithm is tested for minimum samples and projected for large data. The classification accuracies using SVM and NB classifiers are shown in Figures 5 and 6.

5.5. Computational complexity

The start time, sampling time and the number of cycles are programmed in the Arduino software. Normally 200 samples per cycle are collected with a size (N) of 2000 for 10 cycles while acquiring the signals via Arduino. Though the computation time for feature extraction takes only 1.57 s and classification time including training of data takes about 6.25 s. Total computation time is estimated to be 7.82 s which is much better compared to an Mishra et al. [28] reported 75 s for training and 0.06 s for testing. The computation

speed can be further increased by using updated processors. On discussing the complexity of our system it is very simple and of low cost. Since we do not require any pre-processing or normalization steps, the computational burden is much reduced. The cost of this real-time PQ analyser setup is very less as even small industries can also make this arrangement to analyse the electrical signals often.

6. Conclusion

Though a lot of methodologies are implemented for the detection of PQ disturbances acquired practically, the proposed method of the feature extraction based on an FTDD and SVM, NB classifiers shows a novel detection. The disturbances like healthy, harmonics, sag, swell, interruption and transients are considered. Thereby, using FTDD for feature extraction and Naïve Bayes for classification shows improved results for a noisy and noiseless signal. This method shows a high potential and capability for detection of PQ disturbances. The major advantage of the proposed system is, the signal does not losses its characteristics while processing since the signal is not at all decomposed to multi-level. FTDD-based feature extraction is effective in simplifying the complexity present in analysing time domain data. It reduces the quantum of feature size thereby reducing the computational burden and processing time. The classifier built based on FTDD + SVM approach is able to achieve 99.11% accuracy where FTDD + NB approach achieves 99.66% for noiseless signals also for noisy signals the accuracy is more than 95.11% for all SNR levels. Also, this method is preferable due to its robustness and less complexity. The cost of Arduino-based PQ analyser is much lesser than the analysers commercially available. This system

Figure 5. Classification accuracies of SVM and Naïve Bayes classifier.

can be easily expanded for three-phase voltage signals also ensure a successful implementation in real-time detection and industrial applications.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

[1] US Canada power system outage task force, Final report on the August 14, 2003 blackouts in US and C; causes and recommendations, April 2004, p. 1–4.

[2] Arrillaga JA, Watson NR, Chen S. Power system quality assessment. New York: John Wiley and Sons; 2000.

[3] Thapar A, Saha TK, Dong ZY. Investigation of power quality categorisation and simulating it's impact on sensitive electronic equipment. In Proceedings of IEEE Power Engineering Society General meeting, 2004, pp 528–33.

[4] IEEE std.1159–2009. IEEE Recommended Practice for monitoring Electric Power quality. IEEE, Inc., NY, USA.

[5] Granados-Lieboerman D, Romero-Troncoso RJ, Osornio-Rios RA, et al. Techniques and methodologies for power quality analysis and disturbances classification in power systems: a review. IET Gener Transm Dis. 2011;5(4):519–529.

[6] Coppola L, Liu Q, Buso S, et al. Wavelet transform as an alternative to the short time Fourier transform for the study of conducted noise in power electronics. IEEE Trans Ind Electron. 2008;55:880–887.

[7] Uyar M, Yildirim S, Gencoglu MT. An effective wavelet-based feature extraction method for classification of power quality disturbance signals. Electr Power Syst Res. 2008;78:1747–1755.

[8] He S, Li k, Zhang M. A real-time power quality disturbances classification using Hybrid method based on S-transform and dynamics. IEEE Trans Instrum Meas. 2013;62:2465–2475.

[9] Lee IWC, Dash PK. S-transform-based intelligent system for classification of power quality disturbance signals. IEEE Trans Ind Electron. 2003;50(4):800–805.

[10] Abdelazeem A, Eldesouky AA, Sallam AA. Classification of power system disturbances using linear Kalman filter and fuzzy expert system. Int J Elec Power Energ Syst. July 2012;43:688–695.

[11] Biswal B, Biswal M, Mishra S, et al. Automatic classification of power quality events using balanced neural tree. IEEE Trans Ind Electron. 2014;61:521–530.

[12] Cho S-H, Jang G, Kwon S-H. Time frequency analysis of power quality disturbances via the Gabor-Wigner transform. IEEE Trans Power Delivery. 2010;25:494–499.

[13] Ganyun LV, Yang Z, Jin Y, et al. A novel method of complex power quality disturbances classification without adequate history data. In Proceedings of IEEE Power and Energy society meeting (PESGM), 2016, pp 1–5.

[14] Sabarimalai M, Manikandan S, Saman Taray R, et al. Detection and classification of power quality disturbances using sparse signal decomposition on hybrid dictionaries. IEEE Trans Instrum Meas. 2015;64 (1):27–38.

[15] Singh U, Singh SN. Detection and classification of power quality disturbances based on time-frequency-scale transform. IET Sci Meas Technol. 2017;11(6): 802–810.

[16] Naderian S, Salemnia A. Method for classification of PQ events based on discrete Gabor transform with FIR window and T2FK based SVM and its experimental verification. IET Gener Transm Dis. 2017;11(1): 133–141.

[17] Kumar R, Shahani DT, Chandra A, et al. Recognition of power-quality disturbances using S-transform-based ANN classifier and rule-based decision tree. IEEE Trans Ind Appl. 2015;51(2):1249–1258.

[18] Al-Timemy A, Khushaba R, Bugmann G, et al. Improving the performance against force variation of EMG controlled multifunctional upper-limb prostheses for transradial amputees. IEEE Trans Neural Syst Rehabil Eng. 2016;24(6):650–661.

[19] Hjorth B. EEG analysis based on time domain properties. Electroencephalogr Clin Neurophysiol. 1970;29: 306–310.

[20] Khushaba RN, Takruri M, Miro JV, et al. Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features. Neural Netw. 2014;55:42–58.

[21] Padmavathi S, Ramanujam E. Naïve Baye's classifier for ECG abnormalities using multivariate maximal time series Motif. Procedia Comput Sci. 2015;47: 222–228.

[22] Abe S. Support vector machines for pattern classification. Kobe, Japan: Springer-Verlag; 2005.

[23] Guyon I, Matic N, Vapnik VN. Discovering information patterns and data cleaning. Cambridge (MA): MIT Press; 1996.

[24] Eristi H, Ucar A, Demir Y. Wavelet-based feature extraction and selection for classification of power system disturbances using support vector machines. Electr Power Syst Res . 2010;80:743–752.

[25] Biswal M, Dash PK. Detection and characterization of multiple power quality disturbances with a fast S-Transform and decision tree based classifier. Digit Signal Process. 2013;23:1071–1083.

[26] Valtierra-Rodriguez M, Romero-Troneoso RJ, Oscornio-Ios RA, et al. Detection and classification of single and combined power quality disturbances using Neural Networks. IEEE Trans Ind Electron. 2014;61:2473–2482.

[27] Moravej Z, Abdoos AA, Pasoki M. Detection and classification of power quality disturbances using wavelet Transform and Support vector machines. Electr Power Compon Syst. 2010;38:182–196.

[28] Mishra S, Bhende CN, Panigrahi BK. Detection and classification of power quality disturbances using S-transform and probabilistic neural network. IEEE Trans Power Delivery. 2008;23:280–287.