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Detection and Classification of Power Quality Abnormality Using S-Transform and KNN Classifier

J.Anishkumar

Electrical and Electronics Engineering, Assistant Prof (SG), Saveetha Engineering College, Chennai, India
janishengg@gmail.com

ABSTRACT:

In this work power quality abnormality present in power supply was detected and classified using S Transform and k-nearest neighbors Classifier (KNN). The S-transform is used in this paper is to analysis of Power Quality abnormalities under the noisy condition of stationary signals and also it has the ability to sense the various types of disturbance accurately. From S-Transform signal ten types of features values like entropy, range, SD is extracted. The K-NN classifier is trained with 500 different types of sample data taken by varying the voltage, frequency etc. The K-NN classifier is tested with 100 different types of sample data. The KNN classifier has high classification accuracy, less calculation time and learning capability and reduction in complexity are improved. The simulation result of S-transform and KNN Classifier are more efficient in both detection and classification power quality abnormalities when compare to the existing techniques.

KEY WORDS: Power quality, S-Transform, k-nearest neighbors Classifier, Gaussian Window

1. INTRODUCTION

Power quality distortion, abnormalities, disturbances are the main problems facing by all the industries, factory, company, houses. Due to the power abnormalities such as Notch, DC offset, THD the electrical equipments cause various problems such as switching loss, life time get reduced, not working properly and not stable. The power disturbances are occur due to various reasons such as when all load in a grid is ON at a time Voltage sag or dip in voltage will occur. Due to L to L fault, L to G fault, Earth fault, DL to G fault, Short circuit the various types of interruption will occur such as long or short interrupts. Nowadays many electronic equipments are used in day today life in all the equipments the converters, inverters, choppers, AC to AC voltage controllers, Matrix converters,Cycloconverters are used this will vary the supply frequency so harmonics are introduced. In all the electrical power supply, these disturbances need to monitored and controlled by various techniques. PQ events detection is one of the most difficult tasks because it has a wide range of disturbance categories. There are various techniques are available and I have taken few literature surveys in this paper for detection and classification of the power quality abnormalities. In [1] the power quality abnormalities are detected automatically and classified using digital signal processing techniques and artificial intelligent system. This method is very much efficient, robust, simple and had high manipulating performance. In [2] the amplitude and slope parameters were extracted from waveform using Kalman filter and discrete wavelet transform (DWT). The detailed digital simulation was conducted to verify the system and computing. This method should have the ability for detection and classification of the PQ events at high accuracy with less computational time. In [3] Wavelet Discrete wavelet transform (DWT) and S-Transform is used to find more number of the features from the waveform. The binary feature matrix is designed for classifying the PQ events. This method is very simple and high computational efficiency and quite promising result. In [4] Wavelet Transform is used to extract the features from disturbance. The RBFNN is used to classify the power quality abnormalities at low price, speed and extensive computation. The PQ events voltage and current variations, such as Volts reduced and fluctuations, momentary interruptions and harmonics. THD are

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classified in this paper [5]. TMS320F2812 DSP processor is used to classify the single and complex disturbance signals. The key characteristic of this paper is three features are used to classify the mixed disturbance signal [6]. The DWT and MRA concepts is presented in this paper [10&11] generates neural network input vector for the Fuzzy-ARTMAP neural network. Modifications were introduced in this paper to make the input data more suitable and adapt for the FANN. The ranges and features are determined for the training function to identify each disturbance individually so that the classification accuracy and performance is improved in higher value. This work is implemented in real time for water pumping station and described the advantages for the classification of disturbance. The performance of FL-PSO shows very good so it can be implemented for online monitoring of power quality problems [12]. The combined techniques performance is accurate, fast and robust in detection and classification.SVM based PSO classifier results shows it has high accuracy and better robust to noise than SVM. So it was used in real time online to classify the power quality events.[17].

2. POWER QUALITY EVENTS GENERATION

In this paper pure sinusoidal signal and various types of power quality abnormality signal such as DC offset, Swell, ,Notch, short time Interruption, 3rd order harmonics, Transients , Sag and Interrupts , Swell and interrupts, Sag with 3rd order harmonics and Swell with 5th order harmonics are generated for different magnitudes and time period using mat lab code. The control parameters and equation for each event in given in Table1 and a sample power quality abnormalities signal is represented in Fig 1 with duration of 0.4 sec, amplitude 1V and frequency 50 Hz. By changing the amplitude, time, frequency and control parameter 200 different signal are generated for each event. In that 100 signals are used training, 50 signals are used for validatation and the remaining 50 signals are used for verification.

Table 1. Models for Power quality events

Signal	Types	equation	Control variable
Normal signal	W1	y=sin(314*t)	-
Pure sag	W2	y=(1-int*((hs (t-0.04)- hs (t-0.14)))).*sin(314*t)	alpha ranges 0.1 to 0.9
Pure swell	W3	y=(1+ int*((hs t-0.04)- hs (t-0.14)))).*sin(314*t)	alpha ranges 0.1 to 0.9
Interruption	W4	w=(1-int*((hs (t-0.04)- hs (t-0.14)))).*sine(314*t)	alpha ranges 0.9 to 1
Harmonics	W5	w= int1* sine(314*t)+ int3*sine(3*314*t)+ in5*sine(5*314*t)+ int7*sine(7*314*t)	alpha3,aplha5, alpha7 range from .05 to .15
Transients	W6	w= sine(2*pi*50*t)+ am*(hs t-t2)- hs (t-t1)).*exp(-t/ty).*sin(2*3.14*fn*t)	fn goes from 300 to 900
Sag with harmonics	W7	w=(1-int*((hs (t-0.04)- hs (t-0.14)))).*(int1* sine(314*t)+ int3*sine(3*314*t)+ int5*sine(5*314*t)+ int7*sine(7*314*t))	del3,del5, del7 range from 0.051 to 0.151,del ranges 00.1 to 0.9

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Swell with harmonics	W8	w=(1+int*((hs (t-0.04)- hs (t-0.14)))).*(int1* sine(314*t)+ int3*sine(3*314*t)+ int5*sine(5*314*t)+ int7*sine(7*314*t))	del3,del5, del7 range from 0.05 to 0.151,del ranges 0.11 to 0.9
Sag with Interrupt	W9	y=(1-int*((hs (t-0.04)- hs (t-0.15)))).*sin(w*t) - ((int1*((hs (t-0.2)- hs (t-0.25)))).*sin(w*t));	alpha ranges 0.1 to 0.9,alpha=0.5; alpha1 = 1;
Swell with Interrupt	W10	y=(1+int*((hs(t-0.04)-hs(t-0.14)))).*sin(w*t) - ((int1*((hs(t-0.2)-hs(t-0.25)))).*sin(w*t));	alpha ranges 0.1 to 0.9,alpha=0.5; alpha1 = 1;

Fig 1. Power quality disturbances signal (a) Normal,(b) Pure sag,(c) long interruption,(d) short interruption, (e) swell disturbance,(f) swell with harmonics

2. S-TRANSFORM

The S-Transform technique purpose is used to convert the time domain power quality disturbance

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signal such as sag, swell, interrupts, harmonics and transient into frequency domain signals. For classification of power signals in time domain signal we can only less information from the signal so it very difficult to classify the signals and also to extract more features after transformation. The S-transform technique is simulated this paper to detect the time distribution of different frequency range is possible. The S transform is used for large class of practical and real time applications, since it has high range of frequency. The power quality abnormality signals are non stationary because the signals vary wrt to supply and load. The various type of S transform window like Gaussian window, the bi-Gaussian window, hyperbolic window is selected for non stationary signal. The width of the window is also changed to get more information from the signal. In this paper we have introduce the fundamental formula of S-transform to convert a time domain power signal into frequency domain power quality signal and the simulation result of normal signal and sag signal is shown in fig 2.

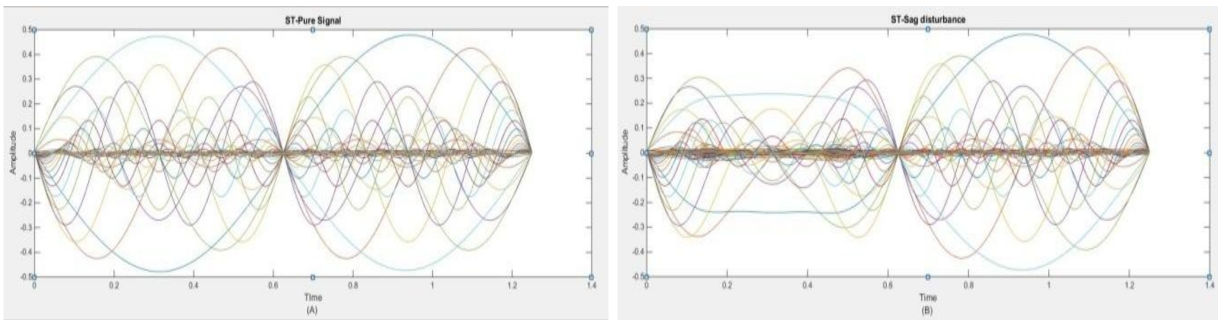

Fig 2. S Transform for power quality disturbances signal (a) Normal,(b) Pure sag

The signal x(t) is described by continuous S-transform as

$$s(\tau, f) = \int_{\infty}^{-\infty} X(t) W(\tau - t, f) e^{-j2\pi ft} dt \qquad (1)$$

Where f represents the frequency of the power signal , $w(\tau - t, f)$ is called as GW function

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

The S transform represented in a matrix format where the rows data’s are used for amplitude and columns are used for frequency information.

The scale factor σ in the signal is termed as:

$$\sigma = 1/|\, f\,| \qquad (3)$$

Width factor is introduce in equ (3) is to perform the GD function in an better way

$$\sigma = \lambda/|\, f\,| \qquad (4)$$

Substitute the equ (4) in equ (1), we get the continuous generalized S-transform output:

$$s(\tau, f) = \int_{\infty}^{-\infty} X(t) \frac{|\, f\,|}{\lambda\sqrt{2\pi}} e^{\frac{-(t-\tau)^2 f^2}{2\lambda^2}} \quad e^{-j2\pi ft} dt \qquad (5)$$

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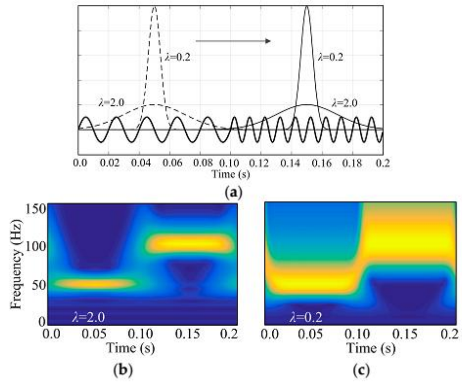

Figure 3. (a) Gaussian windows (b,c) Frequency spectrum signals

The values of f and τ is subsuited to obtain the discrete generalized expression

$$\begin{cases} S\left[mT, \frac{n}{NT}\right] = \sum_{k=0}^{N-1} X\left[\frac{k+n}{NT}\right] e^{\frac{-2\pi^2\lambda^2 k^2}{n^2}} e^{\frac{i2\pi mk}{N}}, \; n \neq 0 \\ S[mT, 0] = \frac{1}{N} \sum_{k=0}^{N-1} X\left[\frac{k}{NT}\right] \qquad , n = 0 \end{cases} \tag{6}$$

X is used to represent in the discrete Fourier transform, the no of sampling points are represented as N,the width of window time interval is noted as T

The features are extracted from the signal using the matrix format

$$A\left[mT, \frac{n}{NT}\right] = \left|S\left[mT, \frac{n}{NT}\right]\right| \quad m, n = 0,1, \ldots.., N-1 \tag{7}$$

4. FEATURE EXTRACTION

The feature extraction of data from the power quality disturbance signal is one of key step to classify the signals. The feature extraction is carried out from the S transform frequency domain signal by applying standard statistical techniques. For power quality abnormality signal classification the accuracy and computational speed is very important .The features used and no of features are key component to improve the accuracy and speed of the classifier. In this paper we have extracted 10 features from the S-Transform signal such as Kurtosis, mean, frequency, Amplitude, Standard deviation, median, variance, smoothness and Skewness etc. In this section I have explained how to calculate the feature from the S transform signal.

F1: Max amp of TmA-plot is calculated by the below equation:

F1 = maximum {TmA(m)} (8)

The max amp in the Y axis and time by searching columns in the X axis of STA is plotted as TmA

F2: Mini amp is measured from the TmA-plot

F2 = min{TmA(m)} (9)

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F3: Mean data is measured from the TmA-plot

$$F3 = \frac{1}{N}\sum_{m=1}^{N} TmA(m) \tag{10}$$

F4: by equation f4, SD is manipulated from the of TmA-plot

$$F4 = \sqrt{\frac{1}{N}\sum_{m=1}^{N}(TmA(m) - F3)^2} \tag{11}$$

F5: From the TmA-plot the maximum and minimum value is added:

$$F5 = F1 + F2 \tag{12}$$

F6: The max and min of the FmA(n) is subtracted to get the maximum difference between Max and Min value

$$F6 = \max(FmA(n)) - \min(FmA(n)) \tag{13}$$

F7: It is used to measure the asymmetry of a random variable in any signal about its mean

The value of Skewness can be +ve, 0,or - ve

The Skewness value is calculated from the FmA-plot:

$$F7 = \frac{1}{(N-1)F6^3}\sum_{n=1}^{N}(FmA(n) - \overline{FmA(n)})^3 \tag{14}$$

F8: The distribution's tails relative and the center of the distribution data are calculated to measure the kurtosis data.

The Kurtosis data is calculated by FmA-plot

$$F8 = \frac{1}{(N-1)F6^4}\sum_{n=1}^{N}(FmA(n) - \overline{FmA(n)})^4 \tag{15}$$

4. K- NN CLASSIFIER

Many neural networks were used to identify the power quality abnormalities in electrical signal but the classification accuracy is not good till now. So I have used a new type of classifier in this paper which performs well for all type of electrical distortion classification and also the accuracy level is also increased. There are two types of learning algorithms are available one is supervised learning and the other is unsupervised leaning. In this paper I have used a K-NN classifier in that the supervised machine learning algorithm is available which perform well for classification and predictive application. The K-NN classifier has two important properties one is lazy and other is non parametric learning algorithm. The lazy learning used all the training data for classification and it does not have any expertise training phase. In non parametric learning algorithm the classification is based on the input data, weight, bias values and it does not assumption.

The K-nearest neighbors predicts the similarity of the data points, assigned data points and closed matched data points from the training algorithm. The working of the K-NN classifier is understand by the below mention steps.

A1 − Load the training and test data to the knn classifier

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A 2 – Select the data values of K which is nearest to the data points.

A 3 – Do the following for all test data

- **A3.1** – Measure the distance between test data and training data
- **A3.2** –The distance values are arranged in ascending order
- **A3.3** − K rows are selected from the sorted array.
- **A3.4** − Assign a class which is most frequently used class of these rows.

A 4 – Terminated

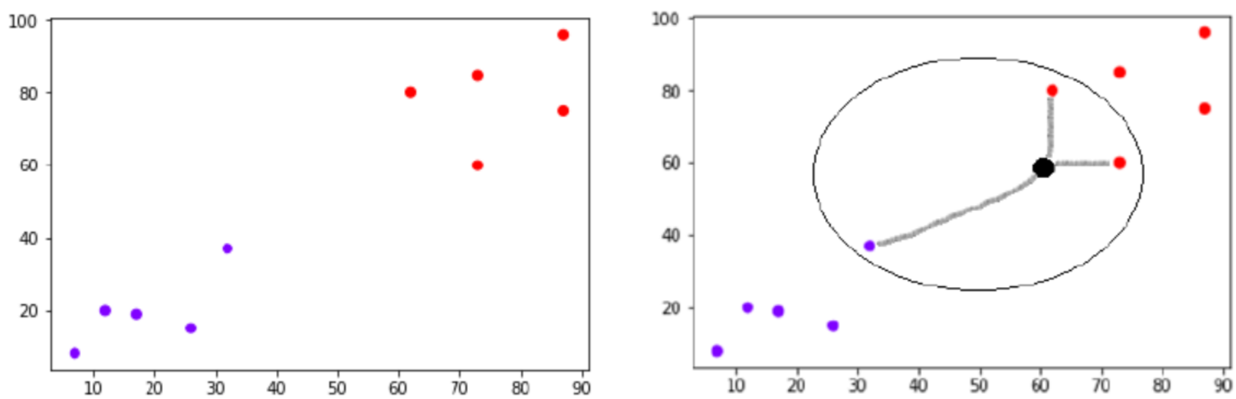

Fig-4.1 working of K-NN classifier

In fig 4.1 explains the working of K-NN classifications. Let us consider or assume the k value as 3 which means it should have 3 points. We have to point a new data point at (60, 60) with a black dot. The black dot is pointed at (60, 60) with 3 nearest neighbour one blue and 2 red. Among this two are red dot class so the red dot class is assigned to the black dot class.

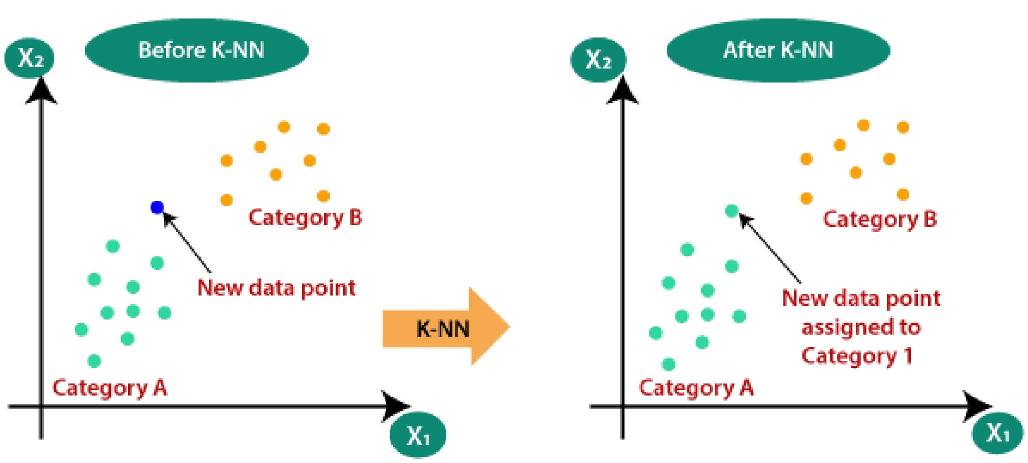

Fig4.2- Assigning new data point

In Fig 4.2 there are two categories are available one is category A and another is category B.A new data point is located in between the two categories. By using the K-NN classifier the new data point should assign a new value**.** In KNN algorithm first step is to choose the k value and assume the k value as 5.we have to find 5 nearest neighbors from all the data point. In category A 3 neighbour are closely matched and in category B 2 neighbour are closely matched. The maximum neighbour are matched with category A so the category A value is assigned to the new data point

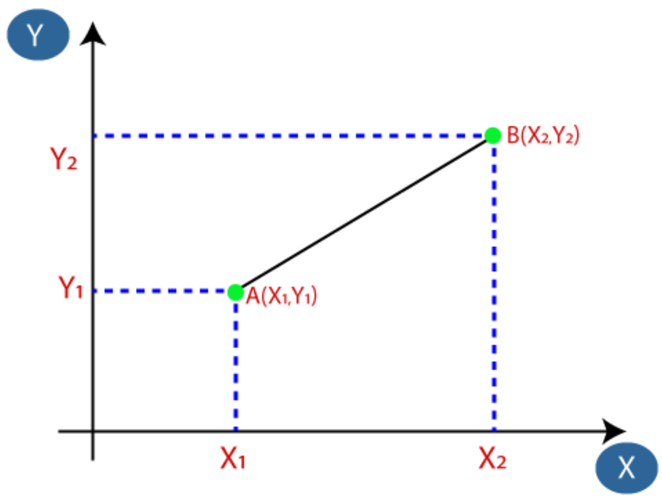

Fig4.3 **-** Euclidean distance calculation

The Euclidean distance between A and B data points was calculated by the formula = $\sqrt{(X2-X1)^2+ (y2-Y1)^2}$

Advantages

- Knn classifier implementation is very simple
- KNN classifer is more effective when the training data is very large

5. RESULT AND DISCUSSION

In table 3 classification accuracy of power quality disturbances is depends upon the events. The normal signal S1 shows the highest percentage of classification accuracy. The swell with interrupt signal S10 shows the least percentage of classification accuracy.

Table 3.Results of K-NN classifier

Signal	Accuracy %
W1	99.23
W2	98.52
W3	98.21

W4	98.22
W5	96
W6	95
W7	95.5
W8	95
W9	94.8
W10	93

From table 4 the accuracy of K-NN classifier is depends on neurons in hidden layer and epochs used for learning. By changing the learning epochs the accuracy has changed only a small percentage. The training accuracy was changed considerably with the number of hidden layer neurons. We have tested the network for various no of hidden layers and the highest training accuracy was achieved by 10 numbers of hidden layers

Table 4. Performance of K-NN Classifier after training

Hidden layer Neurons	Learn epochs	Accuracy in training %
6	1000	95.4
6	2000	95.8
8	1000	96.9
8	2000	97.3
10	1000	98
10	2000	98.3

In this paper I have selected maximum of 10 features from the S- Transform signal such as Kurtosis, mean, frequency, Amplitude, Standard deviation, median, variance, smoothness and Skewness etc for the training purpose. In this paper only four features were taken first and calculated the performance of accuracy it is only 94.4 %.Then no of features were increased by six and calculated the performance of the accuracy it is increased gradually. The performance of accuracy is calculated with max no of features. The results shows when the no of feature is increased the classification accuracy is increased

Table 5. Performance of K-NN Classifier with no of features

No of Features	Classification Accuracy %
04	94.4
06	95
08	95.5
10	95.8

In this paper we have taken ten different types of power quality disturbances. Each disturbance events was named as S1 to S10. A ten cross ten matrixes was formed for target output. In table 6 the rows represent the power quality events and the columns represent the target output of each events. Each event 100 samples were taken by changing the amplitude time and other parameters. Each event 50 samples were taken input and another 50 samples for validation and testing. The KNN classifier is trained with the input

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data and target output.

Table 6. Target Output of K-NN Classifier

Events	Target Output								
W1	8	5	5	5	5	5	5	5	5	5
W2	5	8	5	5	5	5	5	5	5	5
W3	5	5	8	5	5	5	5	5	5	5
W4	5	5	5	8	5	5	5	5	5	5
W5	5	5	5	5	8	5	5	5	5	5
W6	5	5	5	5	5	8	5	5	5	5
W7	5	5	5	5	5	5	8	5	5	5
W8	5	5	5	5	5	5	5	8	5	5
W9	5	5	5	5	5	5	5	5	8	5
W10	5	5	5	5	5	5	5	5	5	8

6. CONCLUSION

A new approach is proposed in this paper to classify the power quality abnormalities by S-Transform and K-NN classifier. The S-transform has lot of advantages compare to other transformation technique like WT,FFT,DFT, etc.The S-transform is applied for noise signal, stationary signal, low voltage signal, high voltage signal, high order harmonics signal. The K-NN classifier main function is used to classify the power quality abnormalities and the results is better when compared with other techniques such as classification accuracy, calculation time, learning capability, computational speed and maximum no of signals are classified. The combination of S- Transform and K-NN classifier technique can be implemented in real time application.

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