Australian Journal of Basic and Applied Sciences, 4(12): 6547-6563, 2010
ISSN 1991-8178

Three Phase Power Quality Disturbance Classification Using S-transform

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Abstract: In this paper s-transform is introduced as an effective method for power quality disturbance recognition. S-transform is a time-frequency analyzes technique that bridges the gap between the short-time Fourier transform and wavelet transform. The features obtained from ST are distinct, understandable and immune to noise. In proposed method by use of s-transform and a decision making algorithm, thirteen types of single Power Quality (PQ) disturbances like sag, swell, interrupt, harmonic, spike, notch, noise, oscillatory transient, flicker, sub-harmonic, DC, inter- harmonic, unbalancy, and two complex disturbances are well recognized. The waves extracted from s-transform let us to investigate PQ disturbances in three phases simultaneously. Therefore disturbances like unbalancy and different sag types can be well recognized. After extracting three features from disturbance signals by means of S-transform, ten distinct indices for each signal will be extracted. By means of these indices and a rule-based decision algorithm various types of PQ disturbances can be classified. For simulation purpose disturbances with random parameters has been produced and for better achiving real conditions they are mixed with noises with different SNR values. It shows that this method can be used for real applications.

Key words: classification, S-transform, power quality, three phase disturbance, sag types.

INTRODUCTION

Nowadays, the electric Power Quality (PQ) has attracted great attention for electric utilities and their customers. Customers in particular have become very sensitive of PQ disturbances because these disturbances degrade the performance and efficiency of their loads. Most of electric equipments are working on the basis of a standard power supply. Having a distorted power supply, they work inappropriately. PQ problem caused by harmonics, over or under voltage, supply interruption, fluctuation, frequency deviation and other violation of variety range of time duration and frequency. To improve electric PQ, source and cause of disturbances must be specified before any mitigating action. The most important task in power quality disturbance recognition is to extract some useful features from disturbance signal automatically. After this, an efficient classification method is needed to classify disturbances automatically using features extracted from them. For each step there are different methods and automated systems that have been mostly used. For feature extraction purpose, Fast Fourier Transform (FFT), (Fusheng, Z. 1999) d-q transform, (Yonghai, X. 2001) and wavelet transform, (Giang, Z.L. 2004; kezonovic, M. 2002) are mostly often used. For the classification process some methods such as Artificial Neural Network (ANN), (Giang, Z.L. 2004; kezonovic, M. 2002; I.W.C. Lee and P. K. Dash, 2003) Fuzzy Logic (FL), (Chilukuri, M.V. 2004) and Support Vector Machine (SVM) (Keawarsa, S. 2008), have been presented in previous works. To analyze PQ disturbances, Short Time discrete Fourier Transform (STFT) is mostly often used. This transform has been successfully used for stationary signals that property of signal does not vary with variation of time. Because of limitation of a fixed window width chosen in advance for nonstationary signals, the STFT does not track the signal dynamic properties. As a result STFT cannot be successfully used for nonstationary signals such as oscillatory transient. Another technique to solve power quality problems is Wavelet Transform (WT) that has some advantages and disadvantages. WT has the capability to extract both time and frequency information from disturbance signal simultaneously. So, it can be used to classify both stationary and nonstationary disturbance signals. Its complicated computations, sensitivity to noise level and dependency of its accuracy on the chosen basis wavelet (Youssef, A.M. 2004) are some disadvantages of using WT for PQ disturbance recognition. The S-Transform (ST) (P.K.Dash, 2003; Fengzhan Zhao, 2007; Ming Zhang, 2008; Hasheminejad, S. 2010) can be seen either as a WT with a phase

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corrected factor or a STFT with a variable Gaussian window and this method has characteristic superior to both WT and STFT. ST can be used for feature extraction stage and it has been combined with other classifiers such as ANN (I.W.C. Lee and P. K. Dash, 2003) and FL (Ming Zhang, 2008) to be used for PQ disturbance classification purpose. All above techniques must be trained. Having insufficient models and cannot be accurate enough. In this paper, the features of PQ disturbances are extracted using ST, and the disturbances are classified using a decision making algorithm. In addition in this method phase and magnitude features of three phase signals are considered. So, proposed method can be used for classification of wide variety range of PQ disturbances as well as unbalancy and types of sag events where three phase of signal must be considered. It is obvious that in the case of single phase loads, considering three phase is a general practice for all PQ disturbances.

II. S-trans Form:

The ST, introduced by Stockwell (R.G. Stockwell, 1996) can be considered as the "phase correction" of CWT. The CWT of function h(t) is defined by (P.K. Dash, 2003):

$$w(\tau, d) = \int_{-\infty}^{\infty} h(t).\, w(d, t-\tau)dt \tag{1}$$

The ST can be presented as CWT by use of a specific mother wavelet multiplied by a phase coefficient:

$$s(\tau, f) = e^{-j2\pi f t}.\, w(d, \tau) \tag{2}$$

Where the mother wavelet w(t,f) is defined as:

$$w(\tau, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}}.\, e^{-j2\pi f t} \tag{3}$$

it will be profitable to know that the scale parameter "d", is the inverse of the frequency (f). Finally, the ST defined as (4):

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) e^{-\frac{(t-\tau)^2 f^2}{2}} e^{-j2\pi f t} dt \tag{4}$$

The ST also can be written as operation on the Fourier spectrum H(f) of h(t)

$$S(\tau, f) = \int_{-\infty}^{\infty} H(\alpha, f)\, e^{-\frac{2\pi^2 \alpha^2}{f^2}} e^{j2\pi\alpha\tau} d\alpha \tag{5}$$

Since S-transform is a representation of the local spectra, Fourier or time average spectrum can be directly calculated by averaging the local spectrum as:

$$H(f) = \int_{-\infty}^{\infty} S(f, \tau) d\tau \tag{6}$$

$$h(t) = \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} S(f, \tau) d\tau \right\} e^{j2\pi f t} df \tag{7}$$

The power disturbance signal h(t) can be expressed in a discrete form as h(kT), k=0,1,...,N-1 that T is the sampling time interval and N is the total sampling number. The discrete Fourier transform is obtained as:

$$H\left[\frac{n}{NT}\right] = \frac{1}{N}\sum_{k=1}^{N-1} h(kT)e^{\left(-\frac{j2\pi nk}{N}\right)} \tag{8}$$

$$n = 0,1,2, \ldots, N-1$$

Using (5), the ST of a discrete time series h(kT) is given by (let $\tau \rightarrow kT \text{ and } f \rightarrow n/NT$

$$S\left[kT, \frac{n}{kT}\right] = \sum_{m=0}^{n-1} H\left[\frac{m+n}{NT}\right] e^{-\frac{2\pi^2 m^2}{n^2}} . e^{\frac{j2\pi mk}{N}} \quad n \neq 0 \tag{9}$$

$$k, m = 0,1,2, \ldots, N-1 \quad n = 1,2, \ldots, N-1$$

$$S[kT, 0] = \frac{1}{N}\sum_{m=0}^{N-1} h\left(\frac{m}{NT}\right) \qquad n = 0 \tag{10}$$

So, the ST matrix S[KT, n/KT] can be used to analyze the PQ disturbances, in which the rows are frequencies and the columns are time values [10]. Each row displays the ST magnitude with all frequencies at the same time, and each column displays the ST magnitude with time varying from 0 to N-1 in the same frequency, where n=0, 1, … ,$\frac{n}{2} - 1$ The ST Amplitude matrix (STA) is:

$$A(kT, f) = \left|S\left[kT, \frac{n}{NT}\right]\right| \tag{11}$$

Besides, having ST Amplitude matrix, considering ST phase matrix can also be profitable to analyze PQ disturbances. This way, phase difference between three phases can be seen.

$$P(KT, f) = \arctan\left(\frac{imag\left(S\left[kT, \frac{n}{NT}\right]\right)}{real\left(S\left[kT, \frac{n}{NT}\right]\right)}\right) \tag{12}$$

III. PQ Analisys Using S-trans Form:

A. Each Phase Independently:

In this paper, thirteen single disturbance signals and two complex signals are considered. They are voltage sag, swell, interruption, oscillatory transient, spike, notch, harmonics, noise, flicker, sub-harmonic, dc, unbalancy, inter-harmonic, sag with harmonic and swell with harmonic. These signals are produced using Matlab software based on mathematical models of PQ disturbances. Fig.1 shows the normal signal and waveforms generated with s-transform. Figs.1-7 show some of these waveforms extracted from s-transform. Figs.1-7(a) shows normal signal and other disturbance signal. Figs.1-7(b) is called Maximum Amplitude Curve (MAC) that is amplitude of STA at each frequency and derived by searching rows of STA at every frequency.

This curve shows the disturbance's frequency components and their maximum amplitude. Where there is a peak on the MAC-curve, there is a main frequency component in the signal. Figs. 1-7(c) is called Standard Deviation Curve (SDC), which shows frequency versus the standard deviation of time values at related frequency in STA matrix. Fig. 1-7(d) is called Fundamental Frequency Amplitude Curve (FFAC), which displays amplitude of time values of STA at fundamental frequency. For normal signal magnitude of FFAC is constant "B" and it's equal to 50. For improving resolution on MAC or FFAC there's a parameter named window Factor (WF). This variable is Gaussian window-width. In this paper for better illustrating various frequency on MAC and SDC, WF is 20 and for better illustrating deviations on FFAC WF is 0.1.

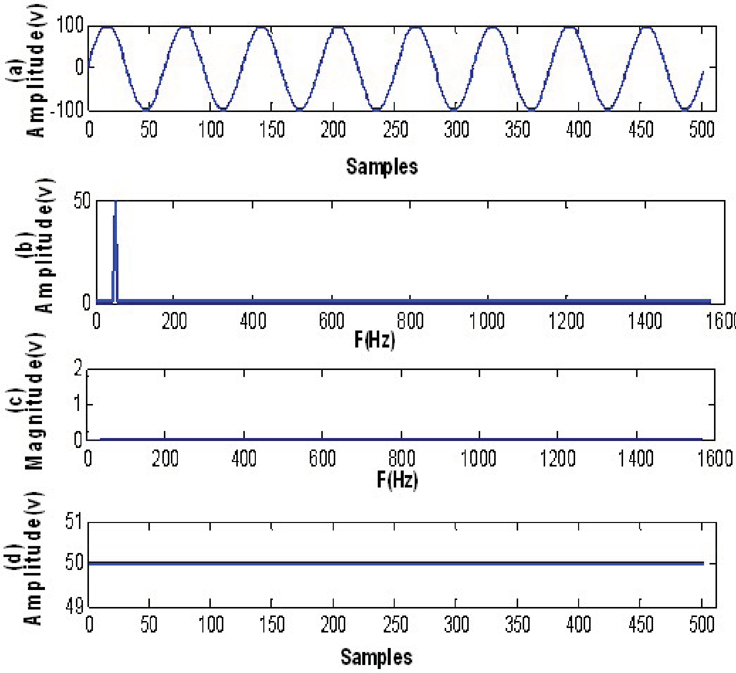


Fig. 1: Normal signal and extracted curves.

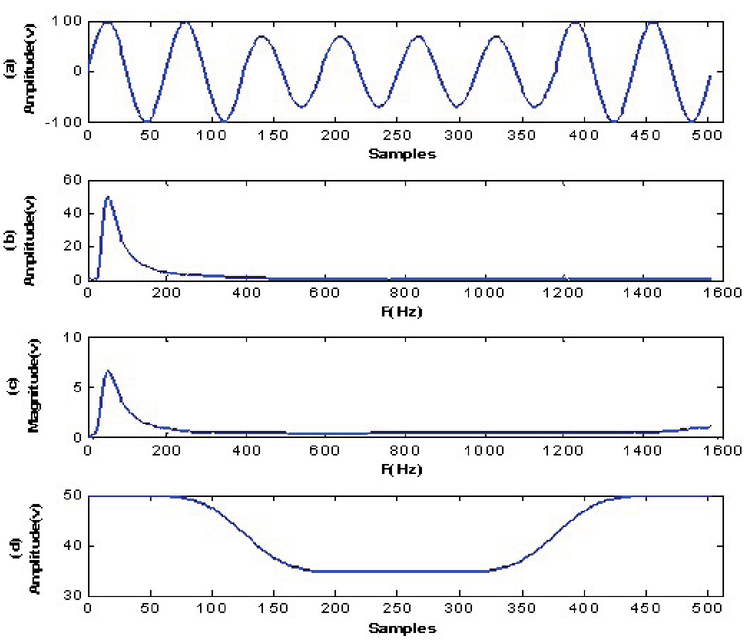


Fig. 2: Voltage sag and extracted curves.

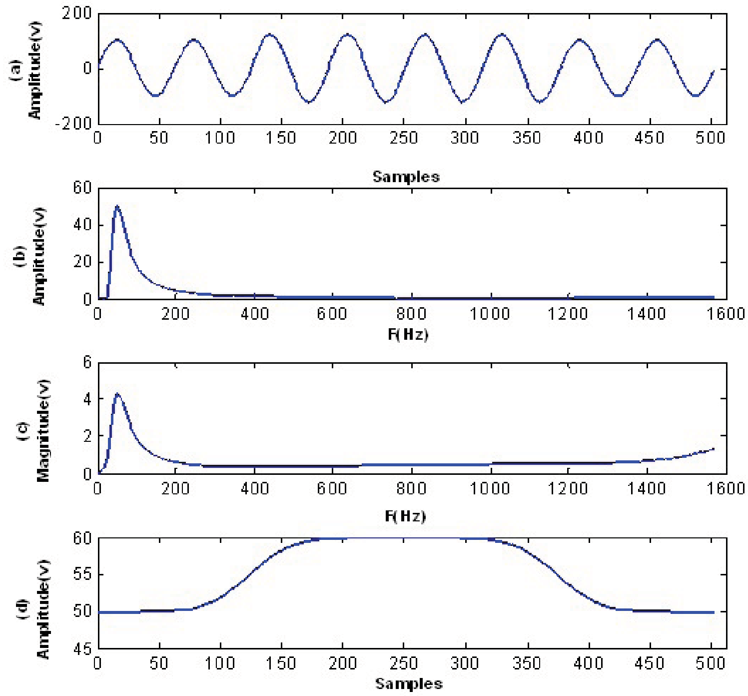


Fig. 3: Voltage swell and extracted curves

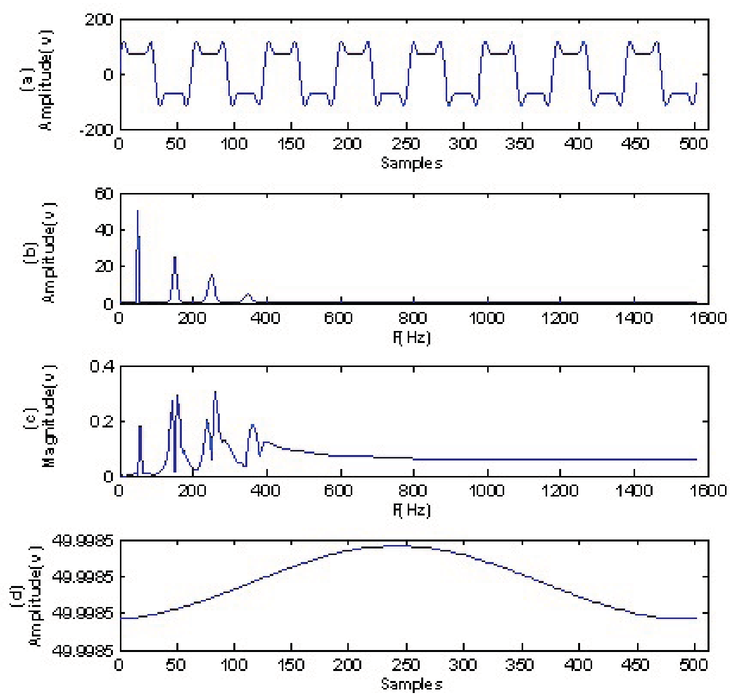


Fig. 4: Voltage harmonic and extracted curves.

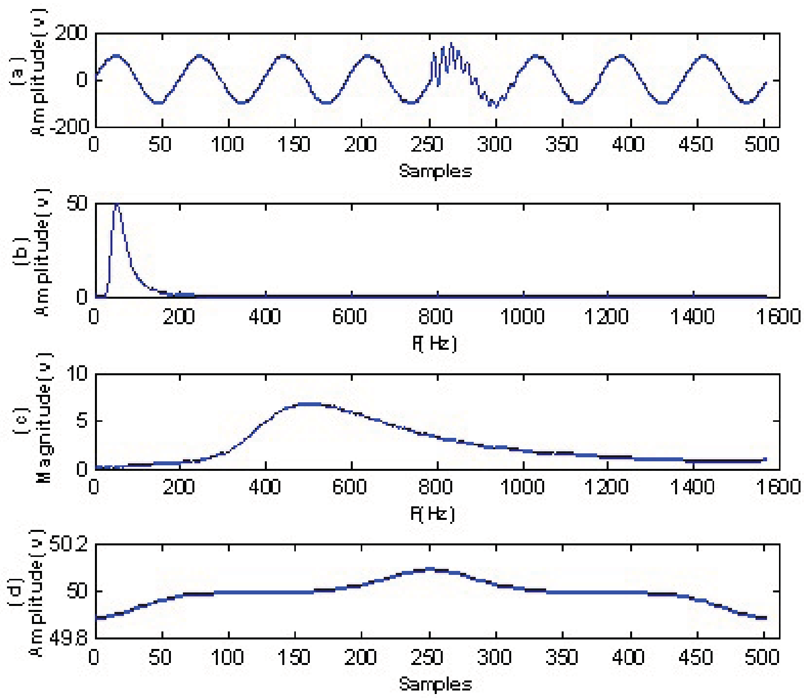


Fig. 5: Oscillatory transient and extracted curves.

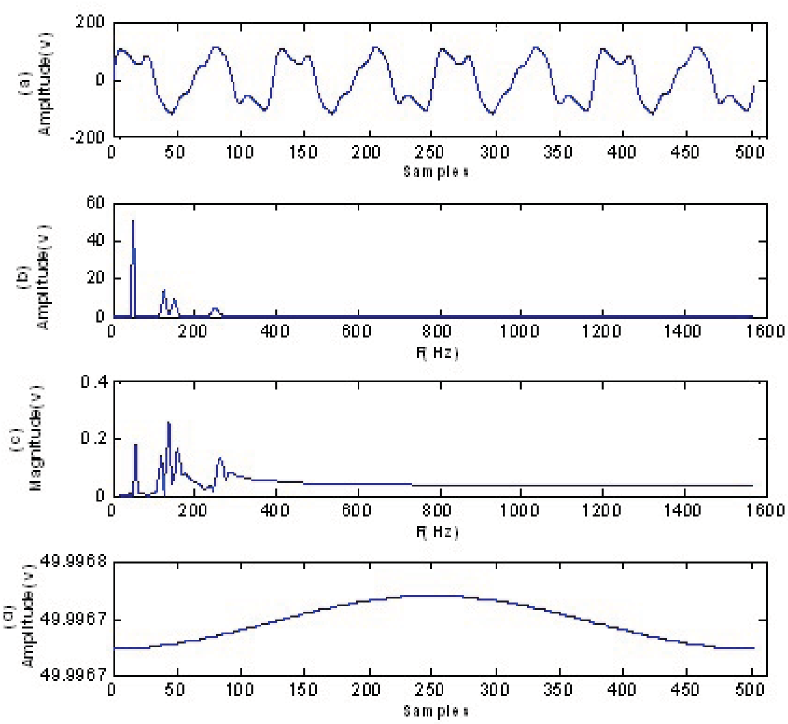


Fig. 6: Voltage inter- harmonic and extracted curves

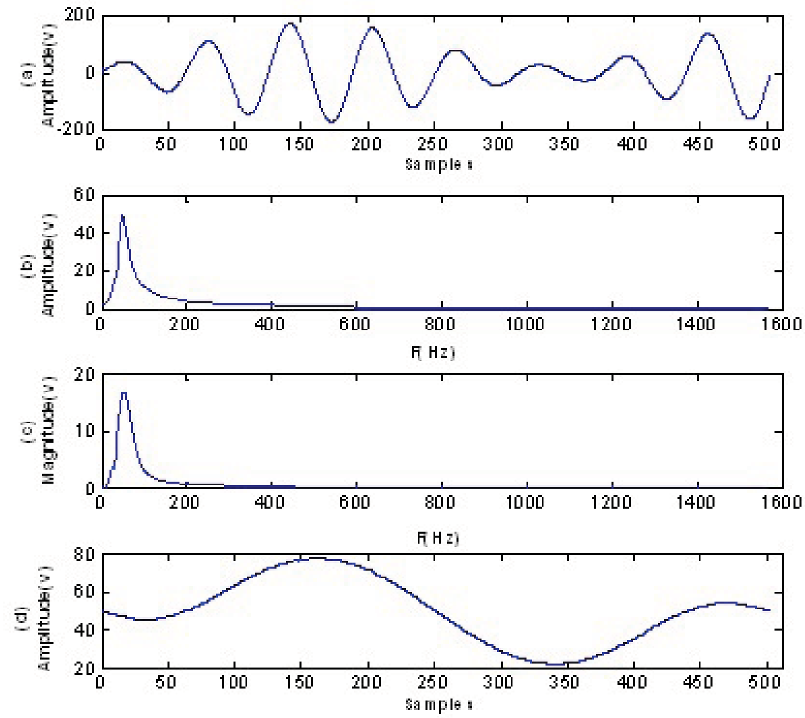


Fig. 7: Voltage flicker and extracted curves

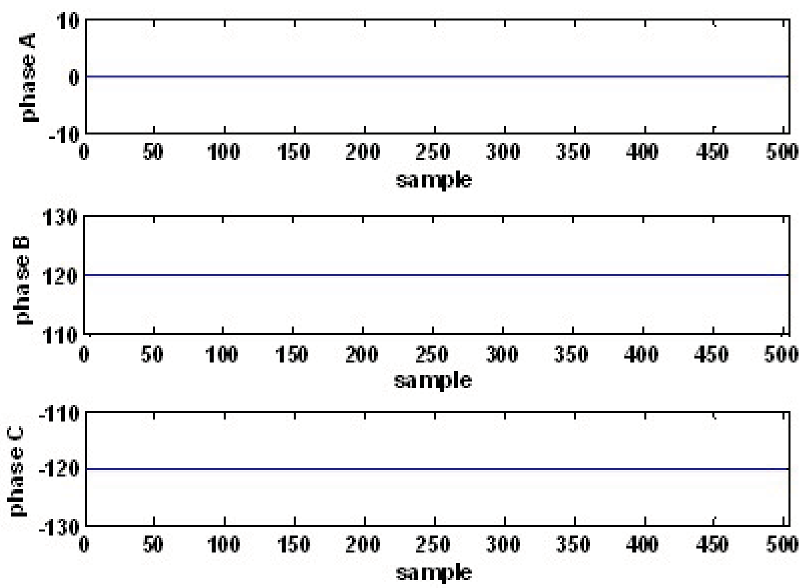


Fig. 8: Phase waveforms for a balanced signal.

B. Three Phases Together:

By the advantage of S-transform the phase waveforms of the given signal can be obtained for three phase simultaneously. It is obvious that for some of PQ disturbances like unbalancy, it is necessary to consider a balance three phase signal phase difference between three phases is 120°. Fig.9 shows phase waveforms for an unbalanced three phase signal. Waveforms obtained from s-transform obviously show the phase shift.

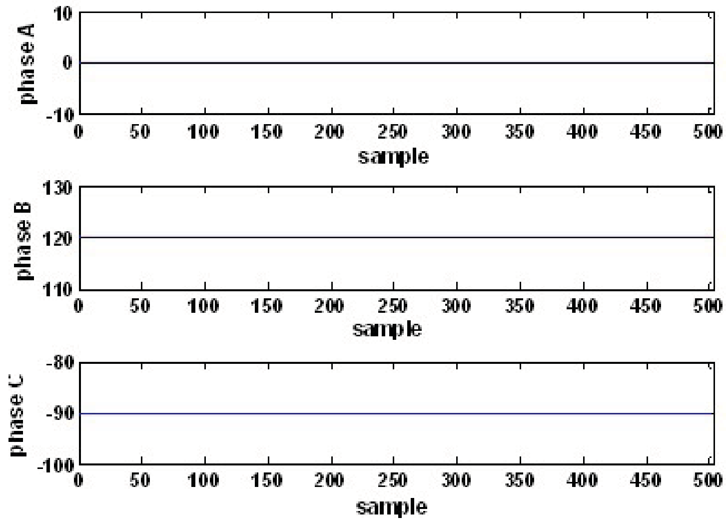


Fig. 9: Phase waveforms for an unbalanced signal.

C. Sag Type Identification:

In addition, using this method various types of voltage sag can be recognized. The differences between wave's amplitude in MAC for three phases or having a difference phase not equal to 120 between three phase curves type of sag can vary from one type to another. Different types of sag are A, B, C, D and E. these types are shown in table (1). It can be seen in table (1), for sag type A, the magnitude is reduced in all three phases and there is no phase shift. For type B, one phase has voltage sag with no phase shift. For type C, there is two phase sag and phase shift in same phases. For type D, there is one phase sag and phase shift in other two phases. And finally for type E there is two phase sag and no phase shift.

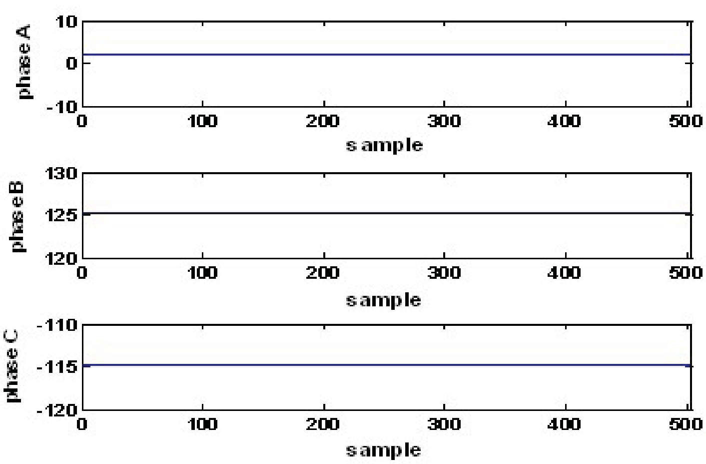


Fig. 10: Phase curves for sag type A.

Figures 10-19 show three phase, phase and amplitude curves for all five types of sag. These figures are extracted using s-transform. With these figures all information about phase and amplitude of a three phase signal is obtained. So, with this information and a suitable decision making algorithm sag types will be recognized effectively and accurately.

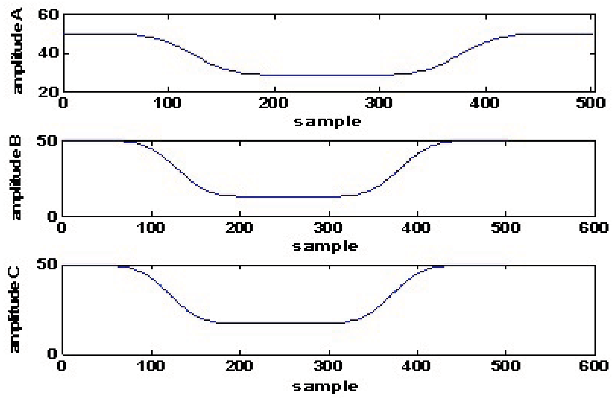


Fig. 11: Amplitude curves for sag type A.

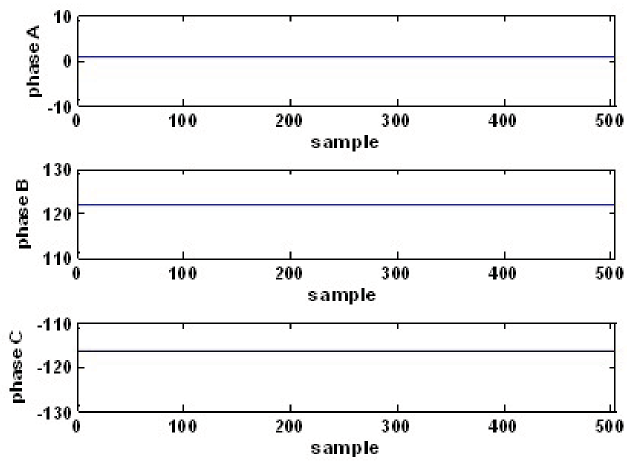


Fig. 12: Phase curves for sag type B.

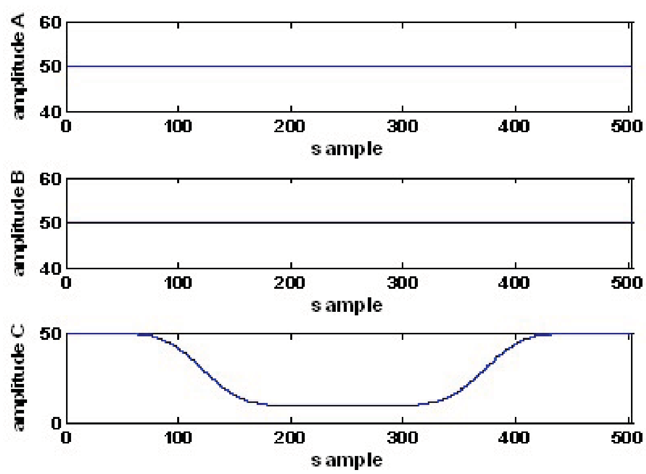


Fig. 13: Amplitude curves for sag type B.

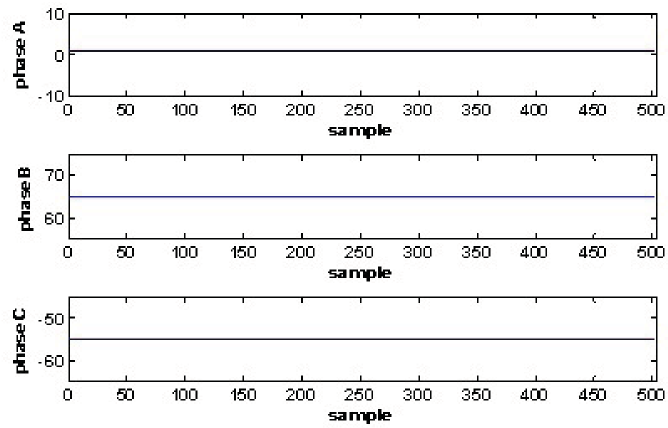


Fig. 14: Phase curves for sag type C.

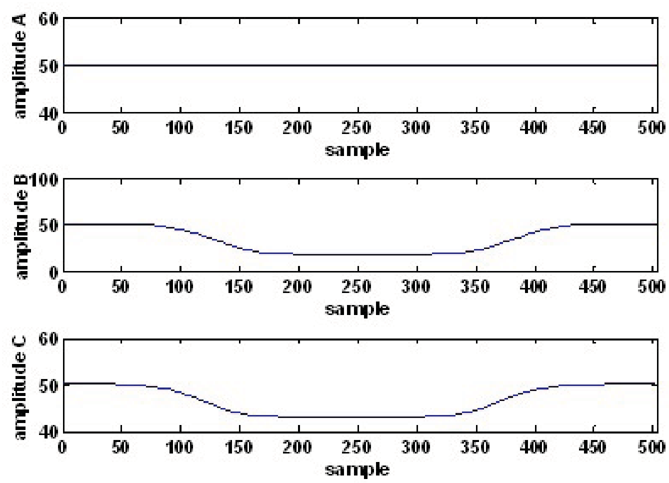


Fig. 15: Amplitude curves for sag type C.

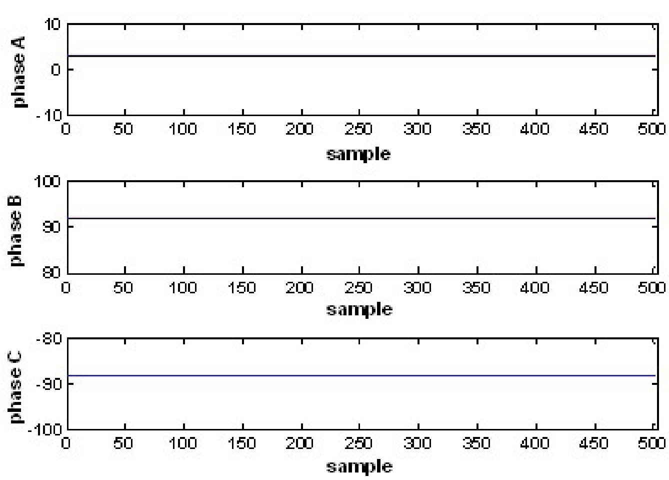


Fig. 16: Phase curves for sag type D.

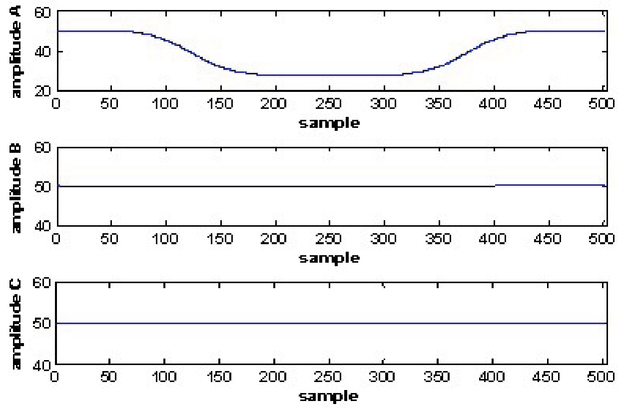


Fig. 17: Amplitude curves for sag type D.

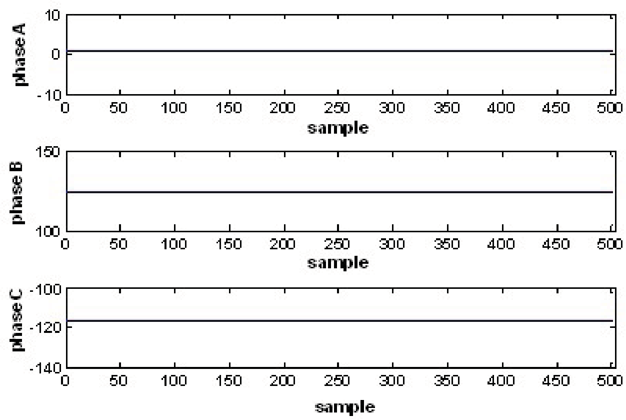


Fig. 18: Phase curves for sag type E.

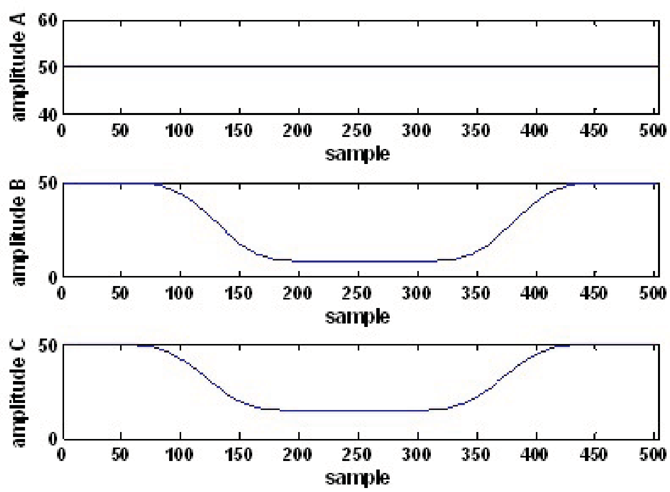


Fig. 19: Amplitude curves for sag type E.

IV. Decision Making Algorithm:

After feature extraction by S-transform, for power quality disturbance classification purpose, the following important features should be extracted from those features:

C_1: the number of peaks in MAC in figs.1-7 (b) that shows the number of frequency components in disturbance signal. So, C_1=1 for signal of sag, swell, interruption, spike, notches, noise and flicker, whereas C_1=2 for sub harmonic and DC, and C_1=3 for the harmonics which has three or more main frequency components.

C_2: having a peak in SDC (figs. 1-7(c)) near the fundamental frequency C_2=1, else C_2=0. So for the signals of sag, swell, interruption, flicker, sag with harmonic and swell with harmonic C_2=1 and for others C_2=0.

C_3: having a peak near a high frequency component in SDC-Curve, C_3=1, else C_3=0. For example for transient signal C_3=1 and for harmonic C_3=0.

C_4: mean of FFAC which is obtained as follows:

$$C_4 = \frac{1}{N}\sum_{k=0}^{N-1} A(f_1, kT) \tag{16}$$

Where k is sampling count, T is the sampling time interval and f_1 is fundamental frequency. In this paper f_1=50Hz and T = $\frac{1}{50\times 64}\,s$

C_5: degree of sag, interruption and swell with four steps which is as follows and for this purpose, the FFAC-Curve of STA is used:

Step 1**:** calculating k_{max} and k_{min}

$$A(f_1, k_{max}T) = max\{A(f_1, kT)\} \tag{17}$$

$$A(f_1, k_{min}T) = min\{A(f_1, kT)\} \tag{18}$$

Step 2**:** calculating R_{max} and R_{min}

$$R_{\max} = \sqrt{\frac{1}{32}\sum_{k=k_{\max}-16}^{k=k_{\max}+15} h^2(kT)} \tag{19}$$

$$R_{\min} = \sqrt{\frac{1}{32}\sum_{k=k_{\min}-16}^{k=k_{\min}+15} h^2(kT)} \tag{20}$$

Where h(kT) is the sampling rate signal

If k_{max}<16 let k_{max}=16, if k_{max}>N-16 let k_{max}=N-16

If k_{min}<16 let k_{min}=16, if k_{min}> N-16 let k_{min}= N-16

Step 3**:** if the disturbance is sag or interruption, then the drop degree is as follows:

$$C_5 = \frac{R_{min}}{R_n} \tag{21}$$

Where R_n is the rms of normal signal. if C_5 <0.1 then the disturbance is the interruption.
If C_5>0.1 and C_5<0.9 then the disturbance is sag.

Step 4: If the disturbance be swelling, then the swell degree is as follows:

$$C_5 = \frac{R_{max}}{R_n} \tag{22}$$

C_6: if there is a peak in MAC on f=0 then C_6=1, otherwise, C_6=0. For example for signal involving DC value in figure 14(b) C_6=1 and for others C_6=0.
C_7: number of peaks on SDC. For example for signal of flicker C_7=1 and for signal of sub harmonic C_7=0.
C_8: for distinguishing inter harmonic from harmonic. And calculate as follows:

$$C_8 = \frac{fre}{50} - \left[\frac{fre}{50}\right] \tag{23}$$

Where [a] is the integer part of digit 'a', and "fre" is the frequency of peak that is occurred in MAC-Curve.

C_9: number of phases that voltage sag occurred on them. This index can be 0, 1, 2 or 3. For example this index for sag type A is 3 and for a balanced signal is equal to 0. This index is used to classify sag types and isn't included in the table.

C_{10}: if there is a phase shift on three phase signal and SDC is not zero this index will be 1, and if there is no phase shift on three phase signal and SDC is not zero, this index will be 0. Besides, if SDC is completely zero and there is a phase shift, this index will be 2. And if the SDC is completely zero and there is no phase shift, this index would be 3. This parameter is used to distinguish noise from unbalancy and normal signal.

According to above simulations, features of fifteen types of power quality disturbances are shown in table II. In this paper d=0.2 and B=50.

According to table II a decision making algorithm can be introduced for classifying power quality disturbances that have shown in figure 14. By the advantage of s-transform not only the signal of sag can be identified accurately, but also type of sag can be recognized. The procedure is depicted in figure 15. As it is shown, the key features are C_9 and C_{10}.
simulation and result

For testing the proposed method, 200 sample signals have been produced for each disturbance signal. For this purpose the key parameters of each disturbance signal are selected and changed randomly. For example magnitude and duration of sags and swells are their parameters.

In addition, for better illustrating the robustness of proposed method, disturbance signals have been mixed with some levels of Gaussian white noise. Gaussian is commonly considered in study of PQ studies. The result of testing process has been shown on table III. Results show the ability of this method to distinguish a wide variety range of power quality disturbances even for real applications.

In table IV, the accuracy of proposed method is compared with some other methods that have been proposed in the literatures. It is necessary to mention that the main benefit of the method is its simplicity for recognition of wide variety range of PQ disturbances with desirable accuracy. For testing the ability of proposed method in recognizing sag types, 200 different three phase disturbance signal is generated for each sag types and the accuracy of proposed method is measured in the presence of high and low level of Gaussian white noise. The obtained results which are appeared in table V show the capability of proposed method for determination of sag types.

Conclusion:

This paper proposes a simple and effective method for classification of fifteen typical power quality disturbances. By using the ST amplitude matrix, ten distinguished time-frequency features of each type of disturbances are extracted. By these features and a decision making algorithm simply and with avoid of complicated methods such as neural networks and fuzzy logic, an accurate and quick system for detection and classification of power quality disturbances has been presented. Moreover, various types of sag is recognized by investigating on three phase of disturbance simultaneously. Simulation result by testing on wide range of PQ disturbances with random parameters and presence of noise shows classification capability. The comparison of results with some previous methods shows an acceptable accuracy.

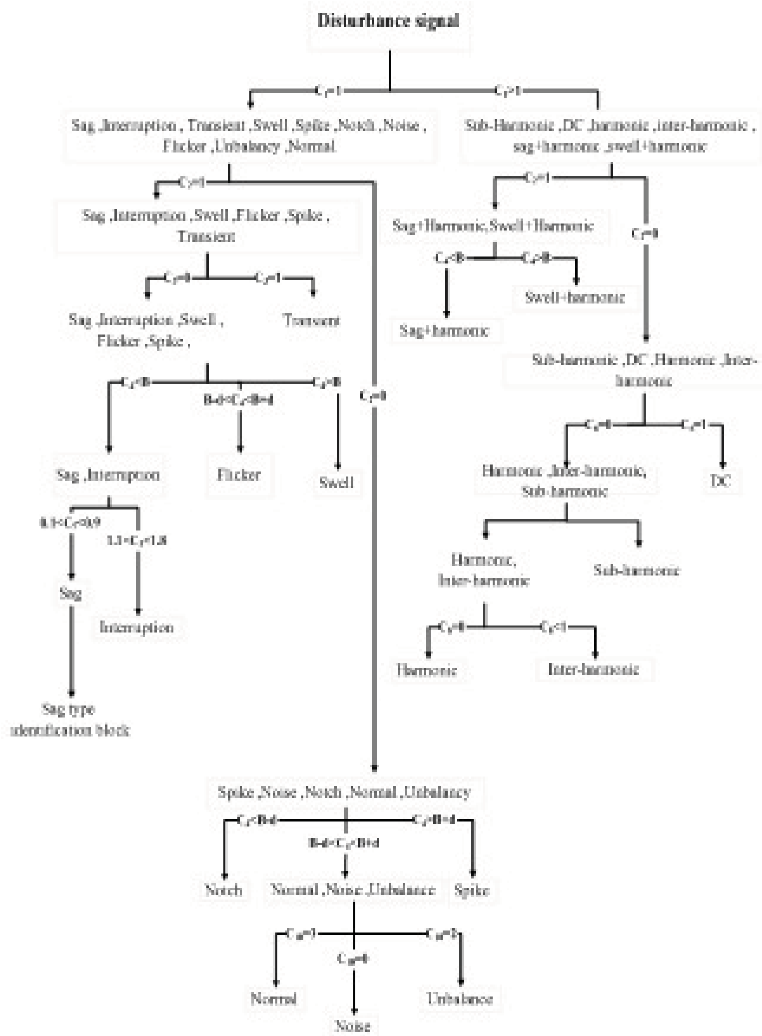


Fig. 14: Decision making algorithm.

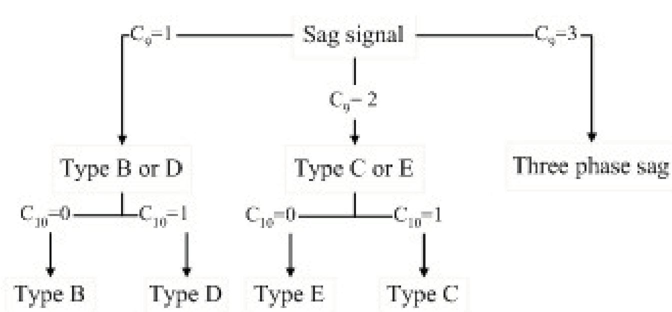


Fig. 15: Flowchart for classifying sag types.

Table I: Various Types of Voltage Sag in Three Phase System

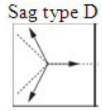
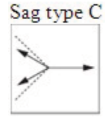
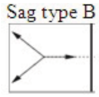
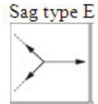
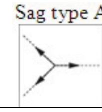
Phase shift	Number of phases stricken to sag		
	1	2	3
Angl	Sag type D 	Sag type C 	
None	Sag type B 	Sag type E 	Sag type A 

Table II: Disturbance Signal Features

Disturbances type	Feature values							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_{10}
Normal	1	0	0	B	1	0	0	0	3
Sag	1	1	-	<B	>0.1 & 0.8>	0	1	0	$\neq 0$
Interruption	1	1	-	<B	<0.1	0	1	0	$\neq 0$
Swell	1	1	-	B>	1.1< & <1.8	0	1	0	0
Spike	1	0	-	>B+d	-	0	0	0	0
Notch	1	0	-	<B-d	-	0	0	0	0
Noise	1	0	-	B-d< & B+d>		0	0	0	0
Transient	1	0	1	-	-	0	1	0	0
Harmonics	>1	0	0	-	-	0	2	0	0
Flicker	1	1	0	b+d>b-d<	-	0	0	0	0
DC	2	0	0	N	-	1	1	0	0
Sub-harmonic	2	1	0	b+d>b-d<	-	0	0	0	0
Inter-harmonic	>1	1	-	-	-	0	2	0<	0
Sag+harmonic	>1	1	-	<B	-	0	1<	0	$\neq 0$
Swell+harmonic	>1	1	-	>B	-	0	1<	0	0
unbalancy	1	0	-	B-d< & B+d>		0	0	0	2

Table III: Classification Accuracy with Different Noise Levels

Disturbancesignal	Accuracy (%)		
	Without noise	SNR=40 dB	SNR=20 dB
Sag	100	100	98
Interrupt	100	97.5	92.5
Swell	100	99	97
Spike	100	99.5	96.5
Notch	100	100	95.5
Noise	96	96	94
Transient	100	100	98
Harmonic	100	100	97
Flicker	100	98.5	95.5
Sub-harmonic	100	99	94
DC	100	99.5	97
Inter-harmonic	100	100	96.5
Unbalancy	100	100	98
Sag + harmonic	100	100	100
Swell + harmonic	100	100	99.5
Average	99.73	99.26	96.6

Table IV: Comparison Between Different Methods

MethodAccuracy	(%)
Wavelet transform and neural network (Santoso, S. 2000)	94.37
Discrete orthogonal S-transform with wavelet support vector machine (Vetrivel, A. 2009)	95.3
Feed forward network (Lee , I.W.C., 2003)	95.33
Probabilistic neural network (Lee , I.W.C., 2003)	95.33
Neural network (M. Kezunovic, 1996)	95.93
Wavelet transform and neural fuzzy (J. Huang, 2002)	96.5

Table IV: Continue.

Proposed method(in the worst case)	96.6
Wavelet pocket and support vector machine (W. Tong, 2006)	97.25
FFT with hidden markov model (T. K. Abdel-Galil, 2005)	97.83
Wavelet transform and hidden markov model (T. K. Abdel-Galil, 2005)	98
Wavelet and fuzzy logic (G. S. Hu, 2005)	98.02
Neural network with DWT and fuzzy logic (M. B. I. Reaz, 1998)	98.17
Discrete wavelet transform and wavelet network (M.A.S. Masoum, 2009)	98.18
Wavelet and fuzzy logic (J. Chung, 2002)	98.70

Table V: Classification Accuracy for Sag Types

Sag type	Accuracy (%)	
	SNR=40dB	SNR=20dB
A	100	95%
B	100	98%
C	100	97.5%
D	100	98%
E	100	97.5%
Average	100	97.2%

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