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Identification of Multiple Power Quality Disturbances using S-Transform and Rule Based Classification Technique

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Abstract: This study presents a relatively new technique for the identification of multiple power quality disturbances recorded in industrial power systems in Malaysia. The new technique, which was developed based on the S-transform and the rule-based classification technique, was evaluated for its' functionality in the identification of both single and multiple power quality disturbances. Sixty numbers of single disturbances and ninety seven numbers of multiple power quality disturbances were used in the evaluation tests. The results of both tests showed that the new technique has a perfect accuracy in the identification of all types of disturbances. Based on these results, this new technique has the potential to be used in the existing on-line power quality monitoring system in Malaysia to expedite the analysis on the recorded disturbance waveforms.

Key words: Disturbances, power quality, PQMS, rule based technique, S-transform

INTRODUCTION

Reducing the number of power quality disturbances has always been the number one critical concern for power utilities around the world because such disturbances can affect the reliability and security of the operations of industrial customers. The most common causes of power quality disturbances are permanent faults in the networks, proliferation of electronic equipment, switching operation of adjacent equipment and improper grounding practices (Kennedy, 2000). If the causes of the disturbances were due to the network operations, these causes would immediately be rectified by the power utility to ensure no repetitions of the same problems again. The information on the actual causes of the power quality disturbances is very important to the plant engineers or technicians that experience sudden production stoppage due to these disturbances. The plant engineer will want to know immediately the type and cause of the disturbance as to whether it is due to their internal systems or the utility network operations. Such information is important for making decision to resume back operation and making report to the management on the type and cause of the disturbance. If the utility's engineers cannot provide the information on the type and cause of the disturbance, then the plant engineers will need to spend time to troubleshoot their internal systems in order to pinpoint the source of the problem. However, the plant engineers do not have much time to troubleshoot the entire plant because it may incurs work stoppage which may cost companies thousands of ringgit (RM) in lost materials and production downtime. Therefore, it is imperative that power utilities implement practical measures to identify the types and causes of power quality disturbances that might originate from the power supply networks.

The most important step in the identification of power quality disturbances is to install an on-line Power Quality Monitoring System (PQMS) at selected substations in the power supply networks (Dugan *et al*., 1996). The PQMS will continuously monitor the condition of the supply networks and immediately provide utility's engineers with related data after the occurrences of a power quality disturbance. With these data, the engineers can classify the types of the power quality disturbances and verify the root causes of the disturbances which would be an essential part in managing these unwanted disturbances. The common techniques used to extract information or features from the recorded waveforms are based on the root mean square (rms) and the Fourier Transform (FT) techniques (Gargoom *et al*., 2005). These two techniques have been proven to be very successful in the past for analyzing stationary signals by providing the magnitude, duration and frequencies of the disturbances. However, most of the disturbance waveforms recorded in the supply networks are non-stationary and co-exist as multiple disturbances only for short duration in time due to the contribution of the network impedances and types of customers loads.

For non-stationary signals, both the rms and FT techniques are not able to track the signals' dynamics properly due to the limitations of fixed window widths (Polikar, 1994). To overcome this problem, advanced

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signal processing techniques have been introduced to analyze non-stationary signals. In recent years, many studies have been conducted using advanced signal processing techniques to extract features that can characterize all types of non-stationary single power quality disturbances. However, the functionality of the signal processing techniques has not been tested for the detection of multiple power quality disturbances that might co-exist in the same voltage signals. According to Bollen and Gu (2006), the ability to detect and classify multiple disturbances in the same voltage signals is an important step for performing diagnosis on the sources and causes of the voltage disturbances. Therefore, it is suffice to say that the detection of multiple power quality disturbances is considered critical for improving the reliability and security of the electrical power networks. In this study, a relatively new technique, which was developed based on the S-transform and the rule-based classification technique, is proposed for identifying the existence of multiple disturbances in power quality measurement data. The performance of the new technique was evaluated based on two tests conducted with actual data obtained from the Power Quality Monitoring System (PQMS) in Malaysia.

The S-transform theory: Signal processing and filtering is, in its modest way, is an attempt to find a better form for a set of information, either by reshaping it or filtering out selected parts that are sometimes labelled as noise. The applications of signal processing techniques in power quality applications is not a new idea, as several researchers have used these techniques successfully in the detection of single power quality disturbances in recorded disturbance waveforms. The interest in exploiting signal processing techniques for analyzing power quality measurement data is due to the fact that signal processing techniques can provide meaningful and valuable information from the recorded voltage and current signals (Bollen *et al*., 2007).

The S-transform is considered as one of the most recent techniques developed for performing signal processing. It produces a time-frequency representation from a time series signal. In mathematics, the S-transform is usually realized as a Laplace Transform. It is also a generalization of the Short-Time Fourier Transform (STFT), extending the Continuous Wavelet Transform (CWT) and overcoming some of disadvantages of the wavelet transforms (Stockwell *et al*., 1996). It can uniquely combine a frequency dependent resolution that simultaneously localizes the real and imaginary spectra. The basis function for the S-transform is the Gaussian modulation cosinusoids. The cosinuosoid frequencies are used for the interpretation of a signal that will result in the time frequency spectrum. In the case of non-stationary power quality waveforms with noisy data, the S-transform can provide patterns that closely resemble the types of disturbances. The S-transform also performs multiresolution analysis (MRA) on a time varying power signal, as its window width varies inversely with the frequency. This will give high time resolution at high frequency and high frequency resolution at low frequency. The S-transform for a function h(t) is calculated by defining a CWT with a specific mother wavelet function multiplied with a phase factor as shown accordingly:

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

Where, the mother wavelet function is defined as:

$$w(t,f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{-i2\pi ft} \tag{2}$$

Explicitly, the S-transform can be written as:

$$S(\tau,f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-i2\pi ft} dt \tag{3}$$

Equation 3 is further simplified as follows:

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

Where, g(τ, f) is the Gaussian modulation function which is given by:

$$g(\tau,f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{\tau^2 f^2}{2}} e \tag{5}$$

The S-transform will also generate time frequency contours, which can display the disturbance patterns for the respective single power quality disturbances. These contours can be used for identifying the existence of single power quality disturbance based on visual observation by Reddy *et al*. (2004). Example of a single power quality disturbance and its' S-transform contours are shown in Fig. 1. In Fig. 1a, the actual voltage disturbance is displayed in its original waveforms and in Fig. 1b the S-transform contours show the existence of the same voltage disturbance between the times of 200-400 msec.

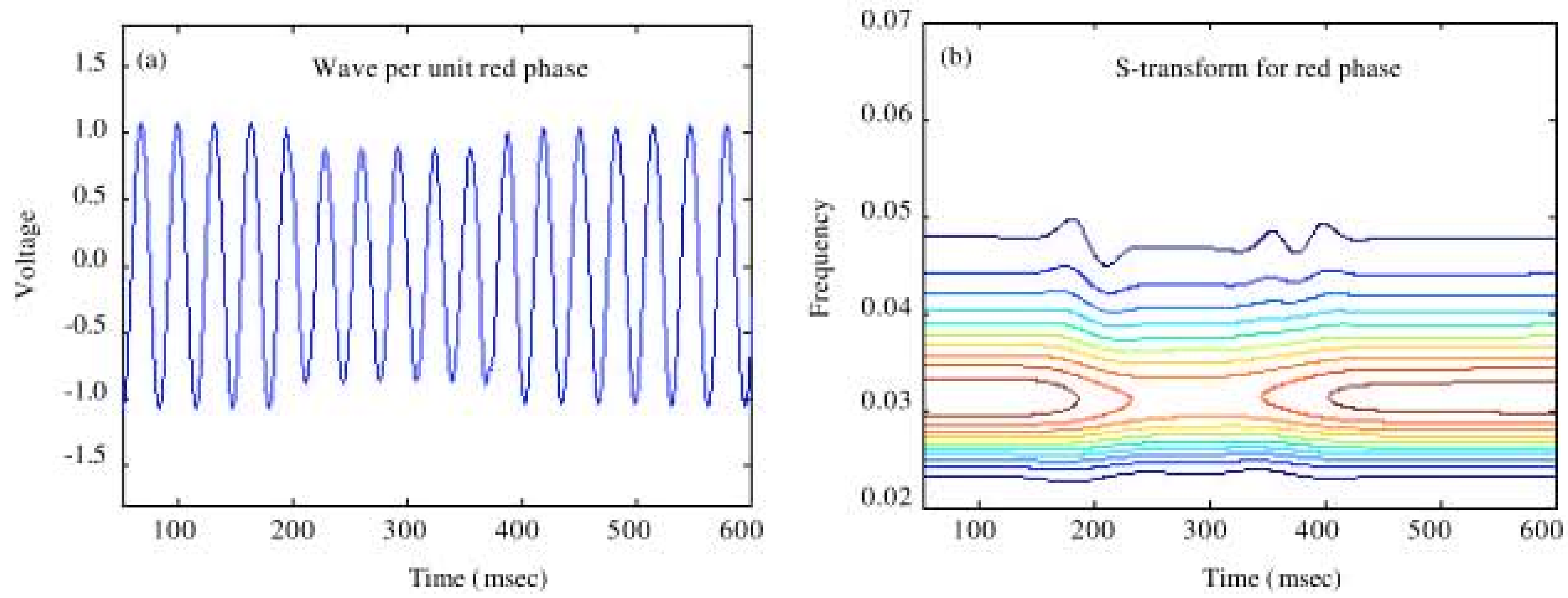

Fig. 1: Voltage sag and S-transform contour for voltage sag detected at the red phase, (a) voltage sag and (b) S-transform contour for voltage sag

THE RULE BASED CLASSIFICATION TECHNIQUE

The most common form of expert systems is a program made up of a set of rules that analyze information (usually supplied by the user of the system) about a specific class of problems, as well as providing mathematical analysis of the problems and depending upon their designs, recommend a course of user action in order to implement corrections (Godoy *et al*., 2007). It is a system that utilizes what appear to be reasoning capabilities to reach conclusions. The Rule-Based Expert System (RBES) is one of the many types of expert systems widely used for performing data analysis. In the past RBES have played an important role in modern intelligent systems and their applications in strategic goal setting, planning, design, scheduling, fault monitoring and diagnosis and so on (Negnevitsky, 2002). Conventional RBES use human expert knowledge to solve real-world problems that normally would require human intelligence. Expert knowledge is often represented in the form of rules or as data within the computer. Depending upon the problem requirement, these rules and data can be recalled to solve problems. Rule-based expert systems have played an important role in modern intelligent systems and their applications in strategic goal setting, planning, design, scheduling, fault monitoring, diagnosis and so on (Chung *et al*., 2002).

In this study, a simple form of the rule-based expert system called the rule-based classifier is proposed for performing classification based on the classes of power quality disturbances shown in Table 1. The six classes of power quality waveforms (C2 to C7) in Table 1 are common disturbance waveforms recorded in industrial power systems.

A rule-based classifier consists of if-then rules, a bunch of facts and an interpreter controlling the application of the rules, given the facts. A rule-based classifier will classify a test record based on the rules triggered by the record. The basic components of rule-based classifier are shown in Fig. 2.

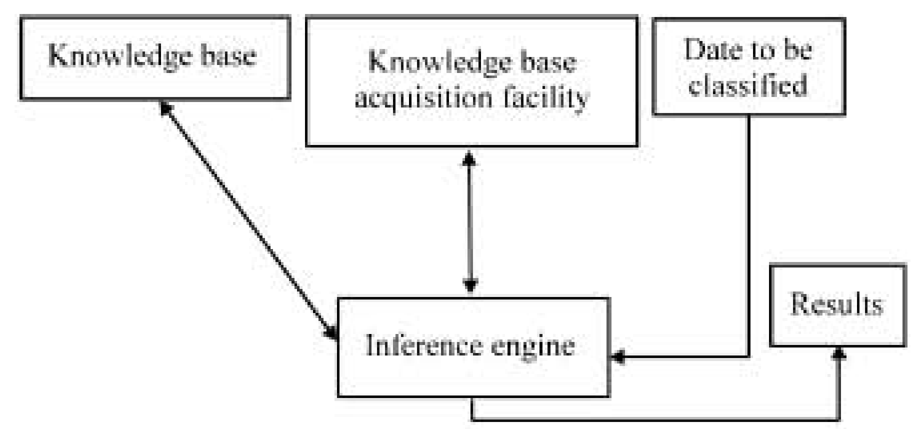

Fig. 2: Architecture of a rule-based classifier

Table 1: Classes of power quality events

Types of power quality disturbances	Classes
Normal voltage (Pure waveform)	C1
Voltage sag	C2
Voltage swell	C3
Harmonics	C4
Notches	C5
Oscillatory transient	C6
Impulsive transient	C7

These if-then rule statements are used to formulate the conditional statements that comprise the complete knowledge base. The knowledge base stores all relevant information, data, rules, cases and relationships used by the classifier system. A knowledge base can combine the knowledge of multiple human experts. A single if-then rule assumes the form if x is A then y is B and the if-part of the rule x is A is called the antecedent or premise, while the then-part of the rule y is B is called the consequent or conclusion. The inference engine used in rule-based classifier is a straightforward method based on the if-then rules. And finally, the results of the classifier will present the classes of the disturbances.

DEVELOPMENT OF THE NEW TECHNIQUE FOR THE IDENTIFICATION OF MULTIPLE POWER QUALITY DISTURBANCES

The new technique for identifying the existence of multiple power quality disturbances in three phase industrial power systems is shown in Fig. 3. The overall structure for the detection and classification processes is based of the structure proposed by Styvaktakis *et al*. (2002) for analyzing single disturbance waveform, where the detection and classification of the disturbance will be performed by a signal processing and a classifier technique, respectively.

In this study, all the three phase power quality disturbance data will be processed by the S-transform. Features that can characterize the power quality disturbances will be extracted from the S-transform. These extracted features will then be applied to the rule-based classifier technique to classify all the cryptic disturbance waveforms. Both the features extraction and classifier technique were developed for identifying both the single and multiple power quality disturbances. The development of the features extraction and classifier is now explained accordingly.

Features extraction using the S-transform: Feature extraction is a unique process that transforms the raw signals from its original form to a new form so that relevant information can be extracted. According to the IEEE 1100-1992, the recommended practice for powering and grounding sensitive electronic equipment, features that are commonly used to classify power quality disturbances are based on four power system parameters i.e., amplitude, frequency, waveforms and symmetry. However, these features are only applicable for analyzing stationary and steady state variations of the three phase voltages and are not applicable for non-stationary waveforms. Another set of features that are also commonly selected to analyze a set of data are based on standard mathematical statistics i.e., maximum, minimum, standard deviation and mean values (Chilukuri and Dash, 2004; Bhende *et al*., 2008). Based on analysis done in this study, the standard mathematical based features are only applicable in the detection of single disturbances. Therefore, the standard mathematical statistics are not applicable in the identification of multiple disturbances.

The S-transform contours can be used to shown the existence of both single and multiple disturbances. The S-transform contours for single disturbance and multiple disturbances are shown in Fig. 4a-c. The original three phase voltage disturbances (1st row) were processed and analyzed using the S-transform and the results are shown in Fig. 4. The results of the S-transform for the red and blue phases depict the existence of only one voltage disturbances i.e., voltage sags, while the S-transform result for the yellow phase showed the existence of two voltage disturbances i.e., voltage sag and a notch. From the graphical results in Fig. 4, it was shown that the S-transform contours can be used to detect both the single and multiple disturbances. The superior properties of the S-transform are due to the fact that the modulating sinusoids are fixed with respect to the time axis while the localizing scalable Gaussian window dilates and translates. As a result, the phase spectrum is absolute in the sense that it is always referred to the origin of the time axis, the fixed reference point. The real and imaginary spectrum can be localized independently with a resolution in time, corresponding to the basis function in question and the changes in the absolute phase of a constituent frequency can be followed along the time axis and useful information can be extracted. The phase correction of the S-transform can also provide significant improvement in the detection and localization of multiple power quality disturbances.

In this study, a new set of features that can characterize both the single power quality disturbance and multiple power quality disturbances was developed based on the S-transform contours. The output of the S-transform is an N×M matrix called the S-matrix whose row pertains to the frequency and columns to time. This new approach for performing detection and classification of power quality disturbances using the time and frequency resolutions is a new and novel approach in feature extraction. Two sets of features are selected from the

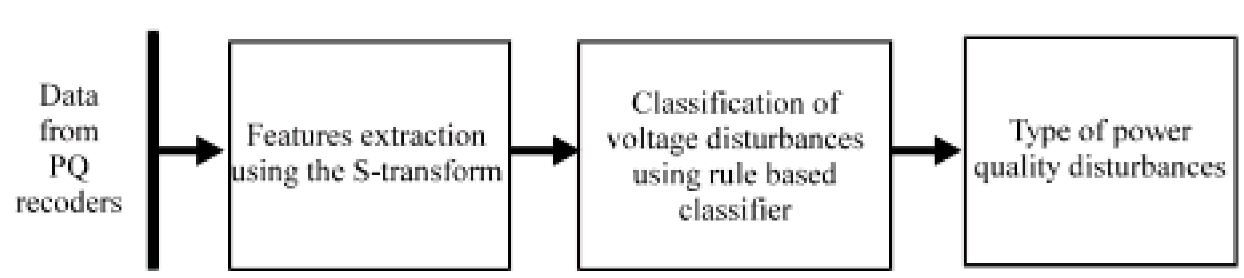

Fig. 3: The new technique for detecting multiple power quality disturbances

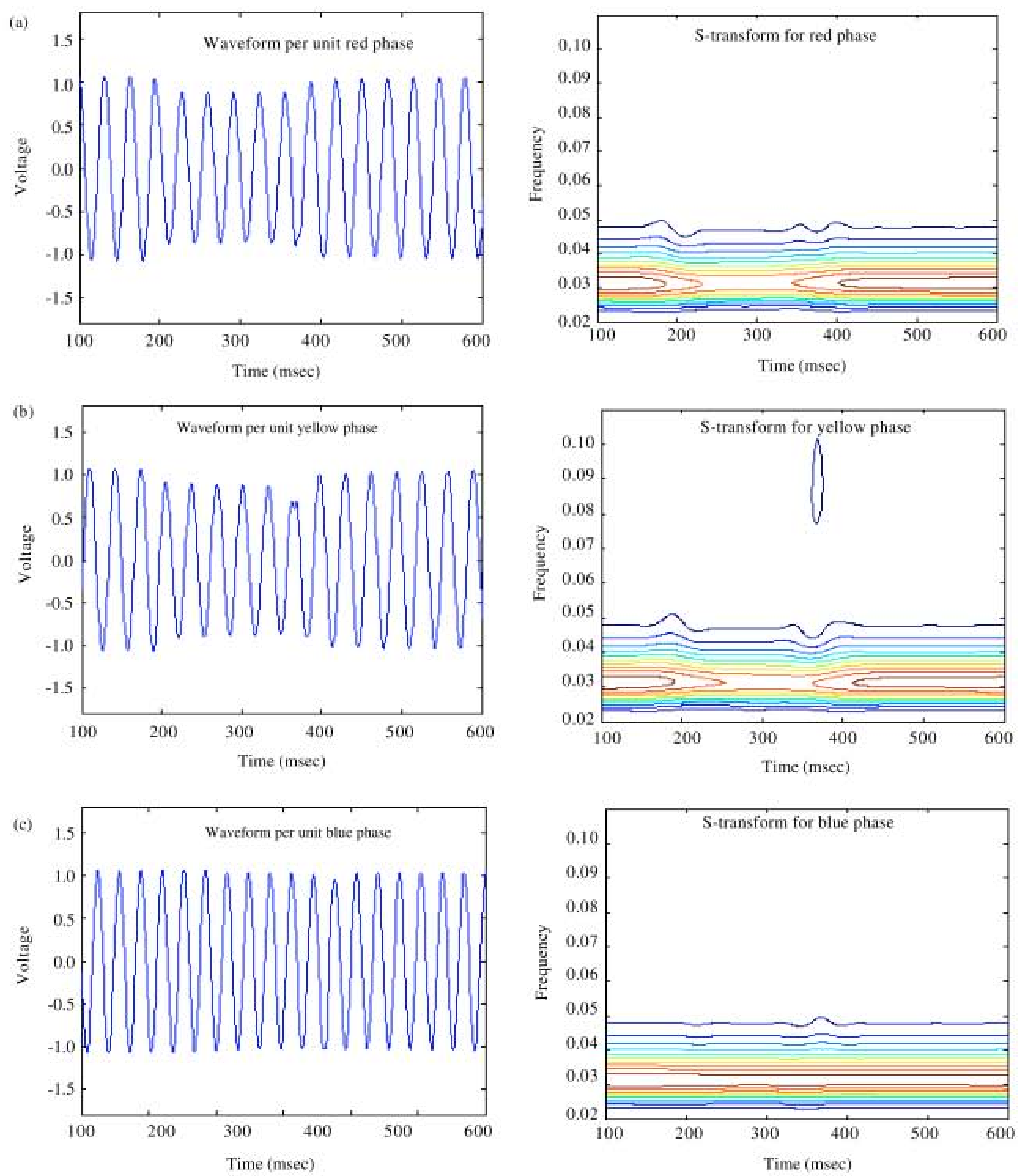

Fig. 4: S-transform contours for single and multiple voltage disturbances, (a) sag, (b) sag and notch and (c) sag

S-matrix. The first set of features was derived based on the maximum values for all the columns in the S-matrix. These features will be used to perform the first classification to distinguish the short duration disturbances (sag and swell) from the other waveforms. It is important to note that the plots of the maximum values of the S-matrix closely resemble the plots of the root-mean-square (rms) values. Comparison between the two plots for the same disturbance data is shown in Fig. 5a-c. In the first row, the original three phase voltage disturbances shown and the plots of the rms values in the respective columns per phase are shown in the second row. The plots in the third row are the locus of the maximum value of the S-matrix.

Four features (F1, F2, F3 and F4) were selected from the maximum value plots. The characteristic of these features were based on the definitions of voltage sag and voltage swell of the IEEE 1159:1995 standard, IEEE

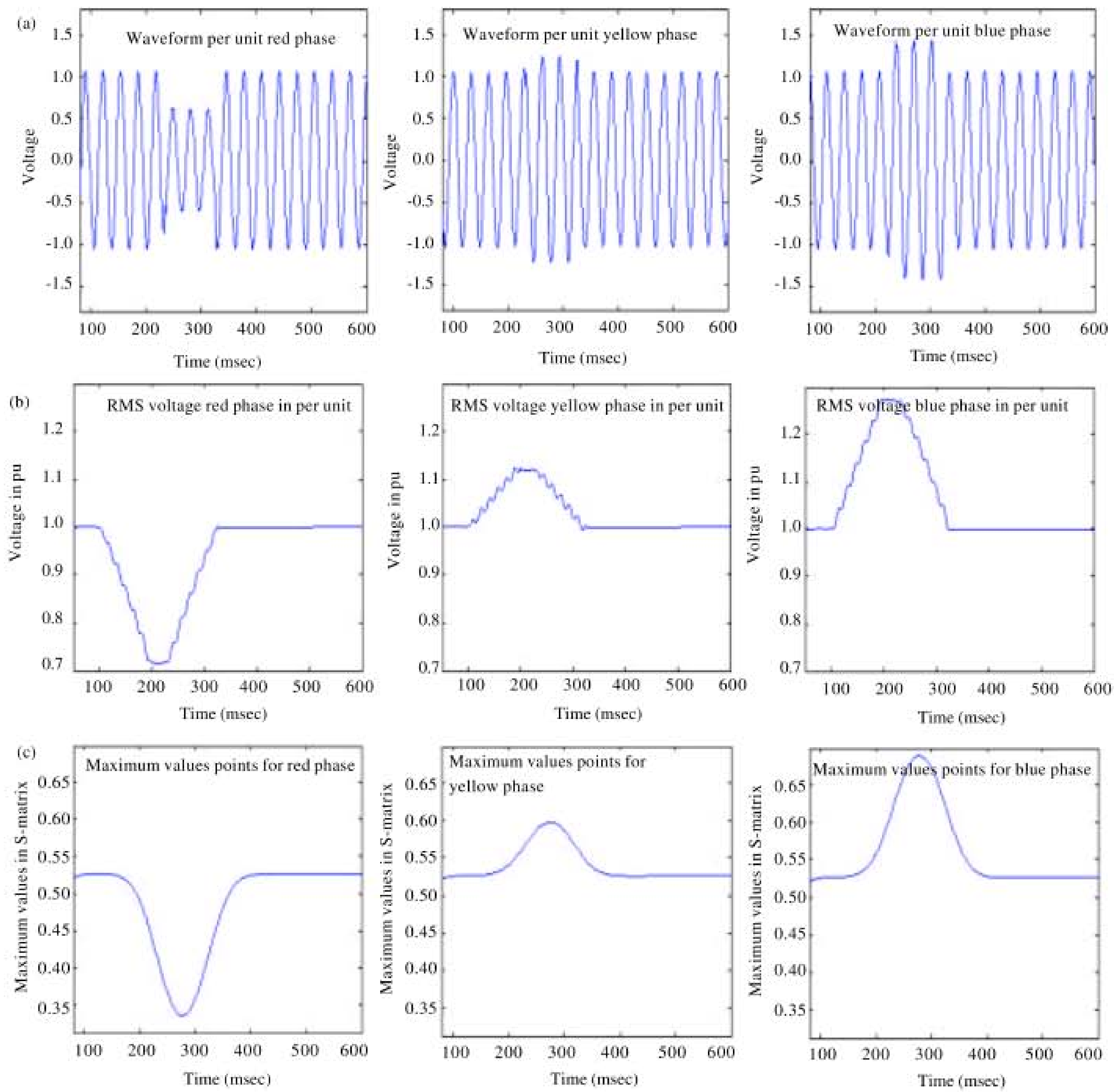

Fig. 5: Comparison between the (a) original voltage signals, (b) plots for root mean square and (c) maximum value plots and for a 1-phase sag (red phase) and 2 voltage swells (yellow and blue phases)

Table 2: Description of features based on the maximum values

Features	Description
F1	Values of time resolution (msec) for the data below the absolute value of 0.90 in the maximum value plots
F2	Values of time resolution (msec) for the data above the absolute value of 1.10 in the maximum value plots
F3	The minimum value below the absolute value of 0.90 in the maximum value plots
F4	The maximum value above the absolute value of 1.10 in the maximum value plots

Recommended Practice for Monitoring Electric Power Quality. The detailed descriptions of these features from the maximum values in the column of the S-matrix are described in Table 2.

The second set of features was developed based on the values of the frequency resolutions in the S-matrix. From the analysis done on twenty four numbers of single power quality disturbances, it was observed that most of the voltage disturbances can be characterized by the values of the frequency resolutions except for voltage sags and swells. The results of the analysis showed that both voltage sags and swells have the same frequency resolution ranging from 0.000 to 0.0061. Harmonics can be

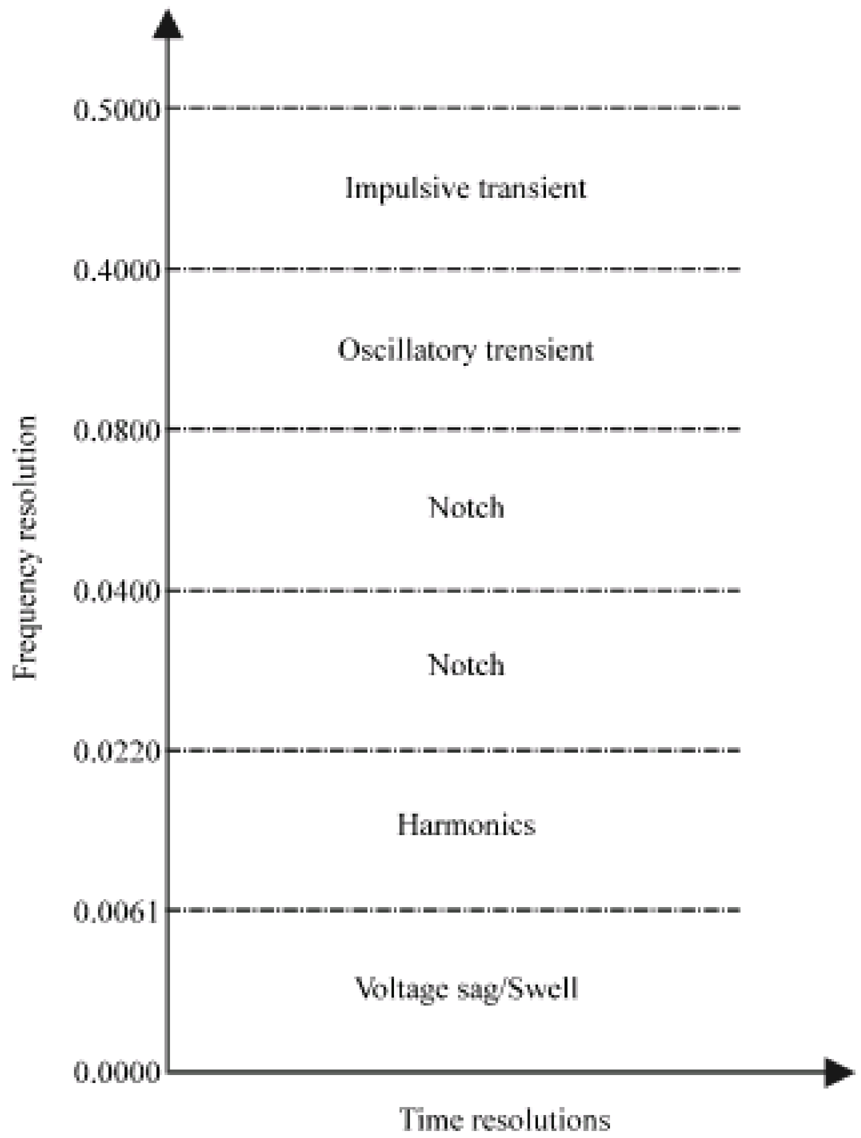

Fig. 6: Features based on frequency resolutions

Table 3: Description of features based on the frequency resolutions

Features	Description
F5	Values of frequency resolution from 0.0061 to 0.022
F6	Values of frequency resolution from 0.022 to 0.04
F7	Values of frequency resolution from 0.04 to 0.08
F8	Values of frequency resolution from 0.08 to 0.40
F9	Values of frequency resolution from 0.40 to 0.50

detected between the frequency resolutions of 0.0061 and 0.022 and notches are detected between 0.022 and 0.080. Oscillatory and impulsive transients can be detected at 0.080 to 0.4 and 0.4 to 0.5 of the frequency resolutions, respectively. The descriptions of all the features selected based on frequency resolutions are explained in Fig. 6 and Table 3.

Classification of power quality disturbances using the rule base classifier. In this study, the objective of the classifier is to classify power quality disturbances based on the definitions of classes shown in Table 1. Referring to Fig. 4, the rule based classifier will classify the recorded waveform either as a single power quality disturbance for example voltage sag (C2) or multiple disturbances comprising of sag and notch (C2 and C5). The procedure and rules to implement the rule-based classifier are shown in Fig. 7, Table 4 and 5, respectively. Two levels of classifications are proposed to ensure perfect accuracy in the classification process. The first level (level 1) classification will be done based on the rules shown in Table 4. The results of the first level classification

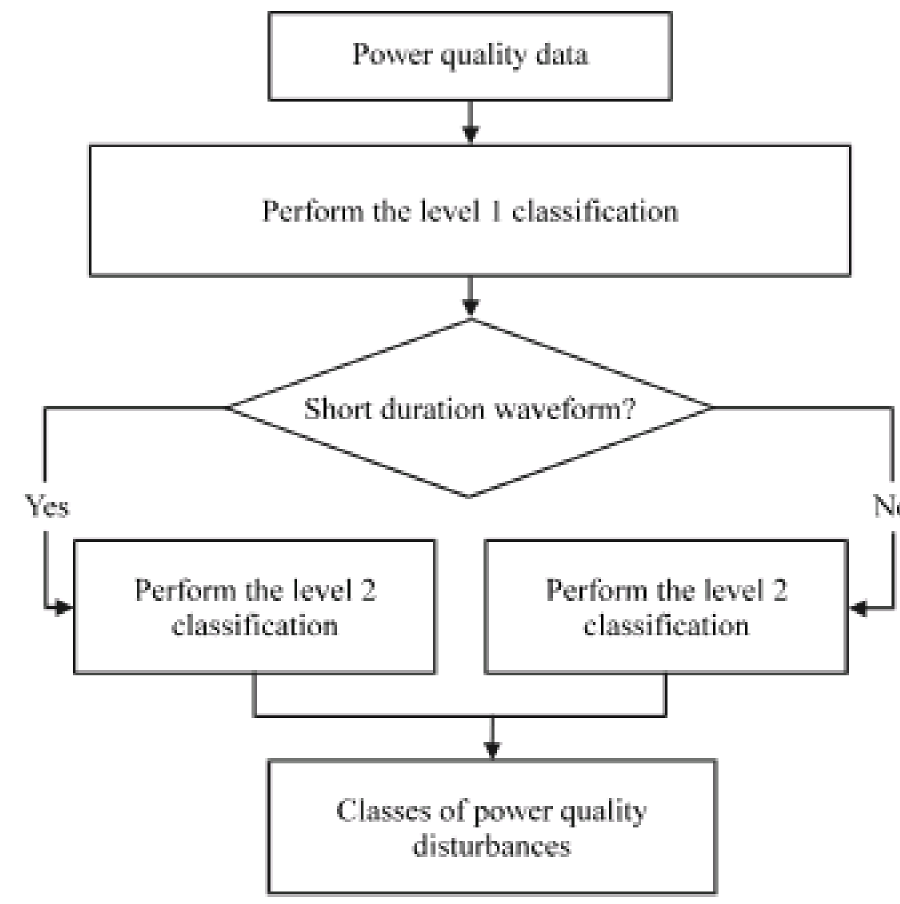

Fig. 7: Procedure for the rule-based classifier

Table 4: Description of rules for level 1 classification

Rules	Description
R1-1 to classify as class 1 (Sinusoidal waveform)	If (F1 = 0) and (F2 = 0), then the signal is detected as pure sinusoidal waveform
R1-2 to classify either as class 2 or class 3 (Voltage sag or swell)	If data is (F1>0) or (F2>0), then the signal is detected as non pure sinusoidal waveform

Table 5: Description of rules for level 2 classification

Rules	Description
R2-1	If (0.90<F3<1.10), (0.90<F4<1.10), (F5 = 0), (F6 = 0), (F7 = 0), (F8 = 0) and (F9 = 0) then data is only C1 (Signal and only contains sinusoidal waveform)
R2-2	If (F3<0.90) and (0.90<F4<1.10), then data is C2. (Voltage sag)
R2-3	If (0.90<F3<1.10) and (F4>1.10), then data is C3. (Voltage swell)
R2-4	If (F5>0) and (F9 = 0) then data is C4 (Harmonic)
R2-5	If (F6>0), (F9 = 0) then data is C5 (Notch)
R2-6	If (F7>0), (F9 = 0) then data is C5 (Notch)
R2-7	If (F8>0), (F9 = 0) then data is C5 (Notch)
R2-8	If (F5 = 0), (F8>0) and (F9 = 0) then data is C6 (Oscillatory transient)
R2-9	If (F5 = 0) and (F9>0) then data is C7 (Impulsive transient)

(level 1) will categorize the power quality data either as short duration waveforms (sag and swell) or other waveform classes. The second level classification (level 2) will be based on the rules in Table 5. It will perform more detailed classification to classify the other waveform signatures that may be encrypted in the same voltage signal.

RESULTS AND DISCUSSION

In this study, the performance of the new technique was evaluated by performing two analyses on two sets of power quality measurement data recorded by the PQMS in Malaysia. The first analysis was conducted to evaluate

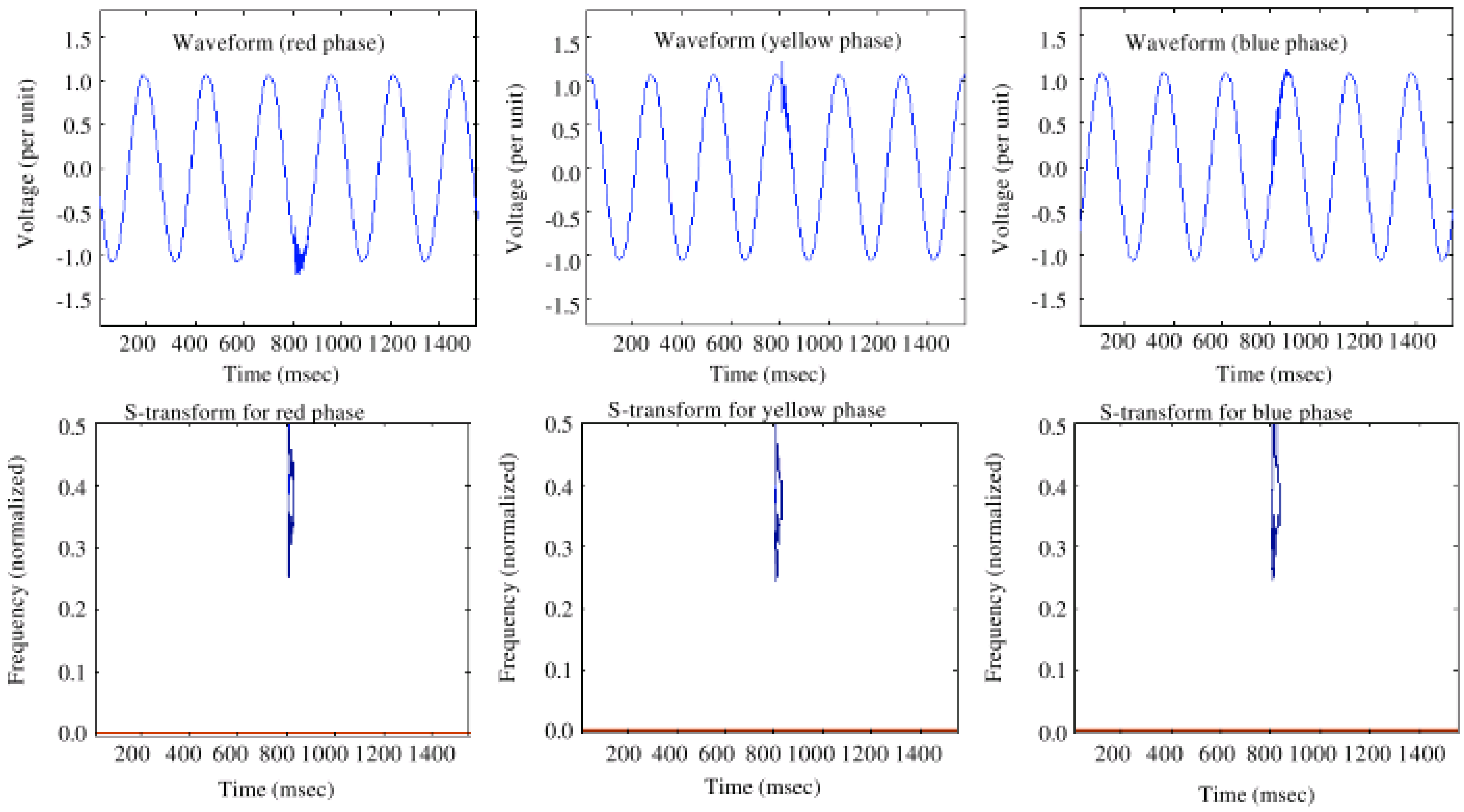

Fig. 8: Results on S-transform contrours for single disturbance impulsive transients

the performance of the new technique in the identification of sixty numbers of single power quality disturbances. And the second analysis was for the identification of ninety seven numbers of multiple power quality disturbances. The results of both analysis were then compared with the results based on visual inspections of the S-transform contours for the same sets of waveforms. The results of the first analysis showed that sixty numbers of single voltage disturbances comprising of sags, swells, harmonics, notches and transients were successfully detected and classified by the new technique with a Classification Accuracy (CA) of 100%. The summary of the classification results of the study are shown in Table 6. Sample S-transform contours for six numbers of single power quality disturbances are shown in Fig. 8, 9a and b. In Fig. 8 and 9, the types of power quality disturbances detected for all the three phases are impulsive, transients and notches, respectively.

The S-transform contours and associated magnitude versus sampling counts and normalized frequency versus amplitudes clearly reveal the signature of the single disturbance patterns. This is due to the fact that the S-transform uses the Fast Fourier Transform (FFT) routine to generate the contours of the disturbance signals. These disturbances are clearly shown, as frequency changes in the contour and, thus, localization of these disturbances and optimal features obtained from them have been used with a rule-based inferencing scheme to provide accurate classification of the power

Table 6: Results on the classification of single power quality disturbances

Type	Description	No. of data analyzed	Classification accuracy (CA) (%)
1	Sags for three phases	10	100
2	Swells for three phases	10	100
3	Harmonic for three phases	10	100
4	Notch for three phases	10	100
5	Oscillatory transient for three phases	10	100
6	Impulsive transient for three phases	10	100
	Total	60	100

quality disturbance waveforms. The results of the first analysis showed that the new technique was able to detect and classify all classes of single disturbance waveforms.

The second analysis for the identification of ninety seven numbers of multiple power quality disturbances also saw the same classification accuracy of 100%. The summary of the classification results of the study are shown in Table 7. Sample S-transform contours for twelve numbers of multiple power quality disturbances are shown in Fig. 10 to 15. The disturbances in Fig. 10 are similar to that of Fig. 4. Voltage sags were detected in the red and blue phases. Two disturbances i.e., voltage sag and notch, were detected in the yellow phase. Figure 11, total of seven voltage disturbances were detected. Three voltage disturbances, a voltage sag, harmonic and notch, were detected in the red phase. Two disturbances, a harmonic and notch, were detected in the yellow phase. And in the blue phase, two disturbances, voltage swell and harmonic, were detected. The rule-based classifier

Table 7: Results on the classification of multiple numbers of power quality disturbances

Type	Red phase	Yellow phase	Blue phase	No. of data analyzed	Classification accuracy (CA) (%)
1	Sag	Sag, harmonic and notch	Pure waveform	23	100
2	Sag, harmonic and notch	Harmonic and notch	Swell and harmonic	22	100
3	Swell	Swell and harmonics	Sag, harmonics and notch	12	100
4	Harmonic and notch	Swell, harmonic and notch	Sags and harmonic	20	100
5	Swell and harmonics	Sag and harmonics	Swell	10	100
6	Harmonic	Harmonic and notch	Harmonic	10	100
			Total	97	100

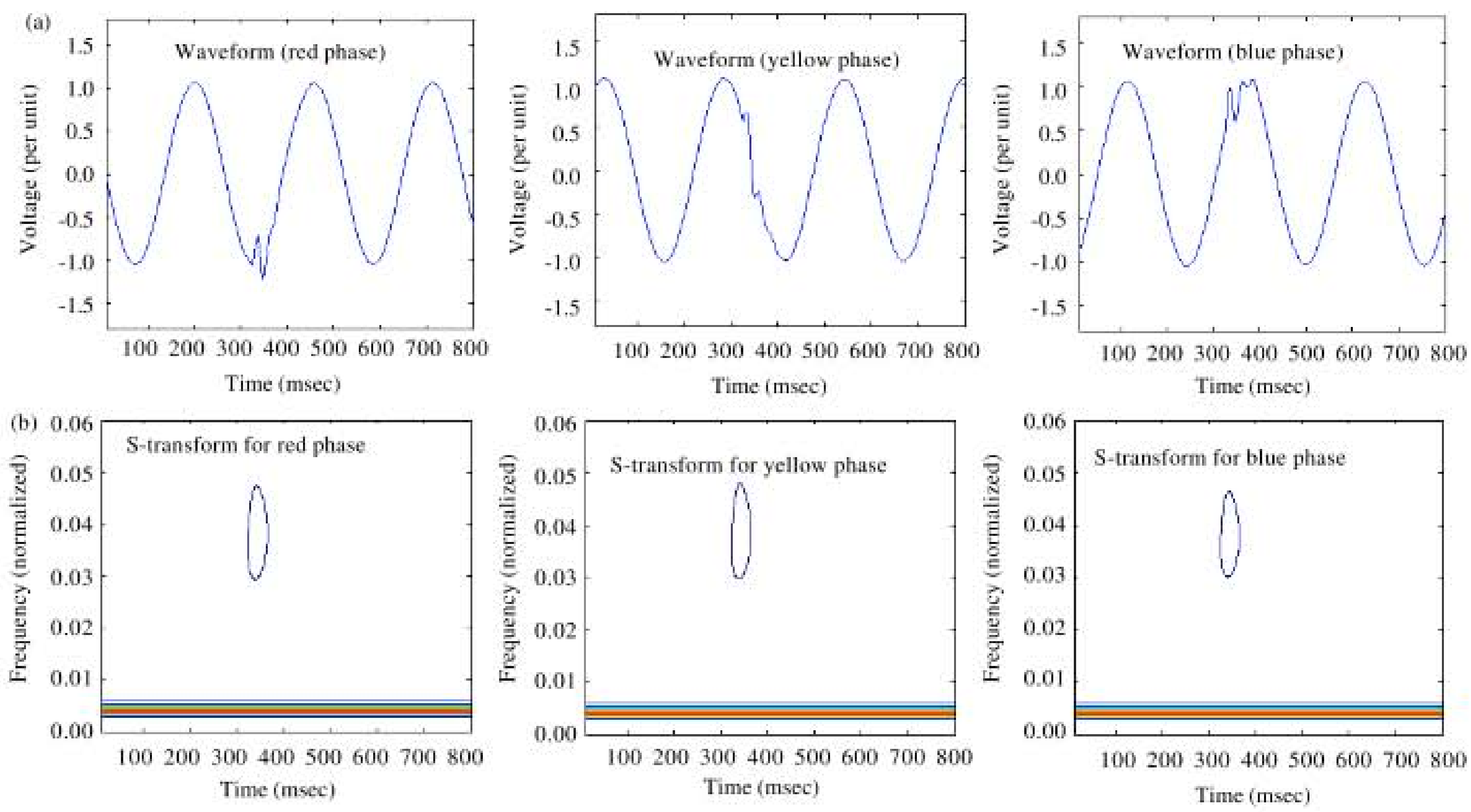

Fig. 9: Results on S-transform analysis for single disturbance-notches, (a) impulsive, (b) transients and (c) notches

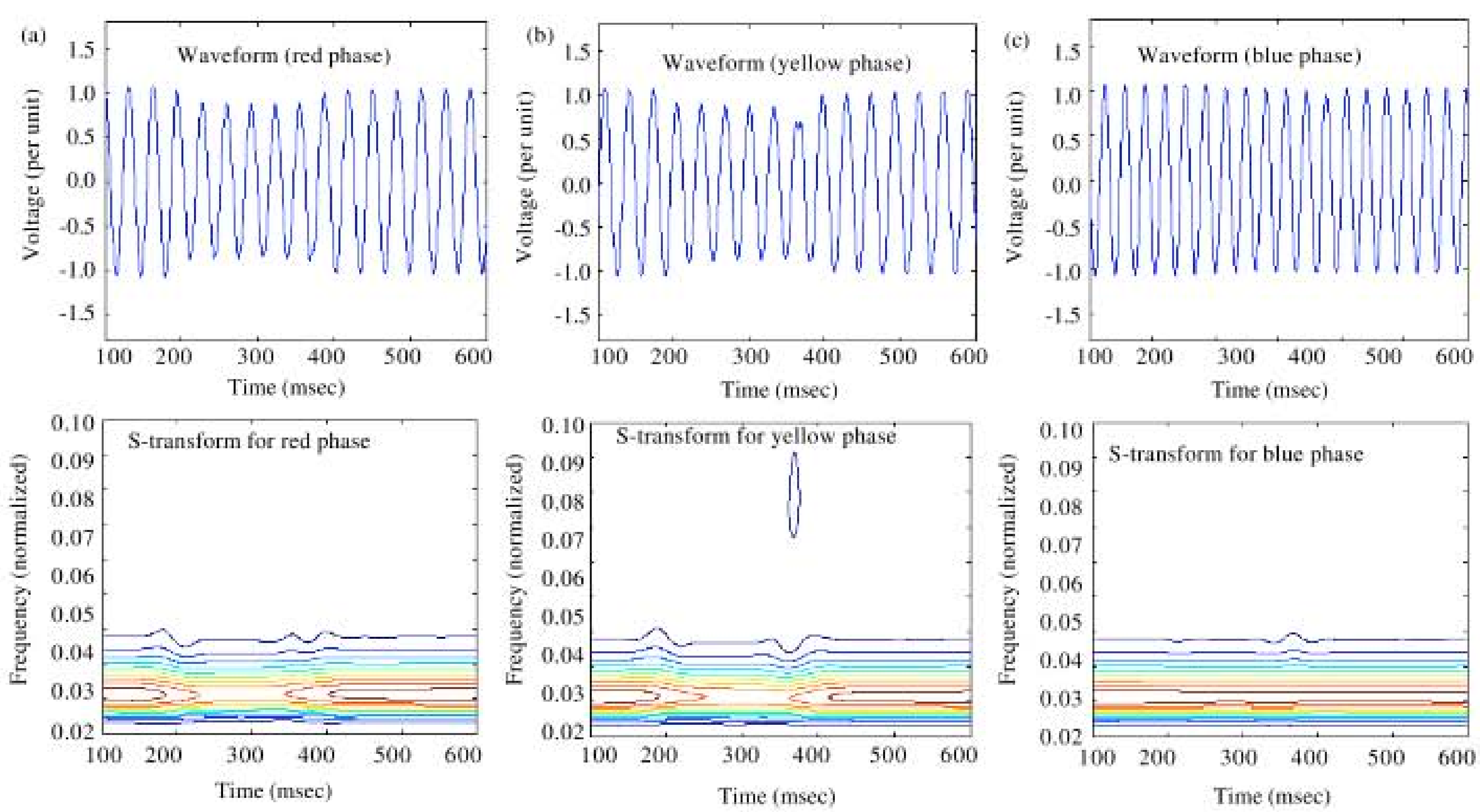

Fig. 10: S-transform contours for multiple disturbance, (a) sag, (b) sag and notch and (c) sag

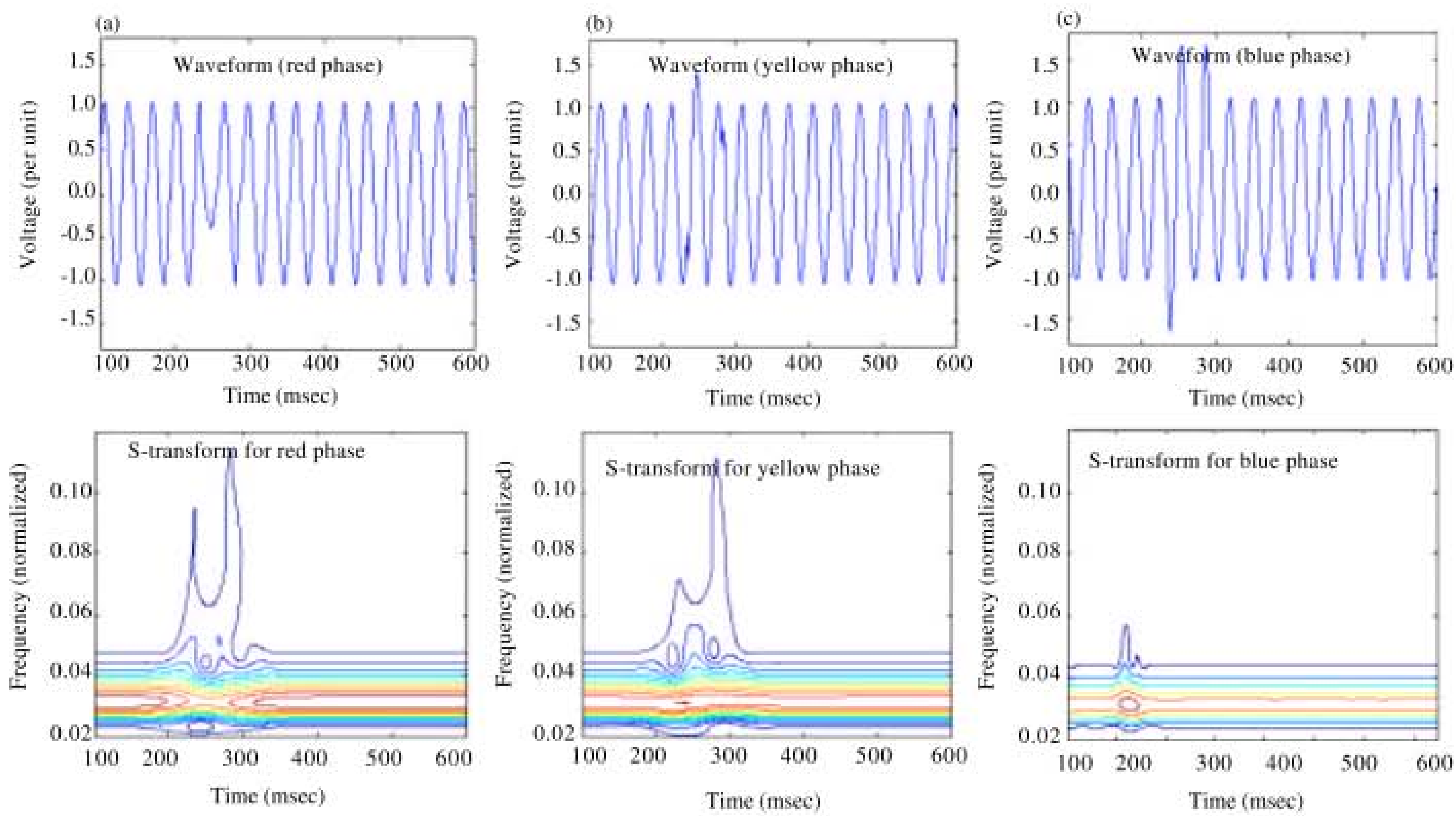

Fig. 11: S-transform contours for multiple disturbance, (a) sag, harmonic and notch, (b) harmonic and notch and (b) swell and harmonic

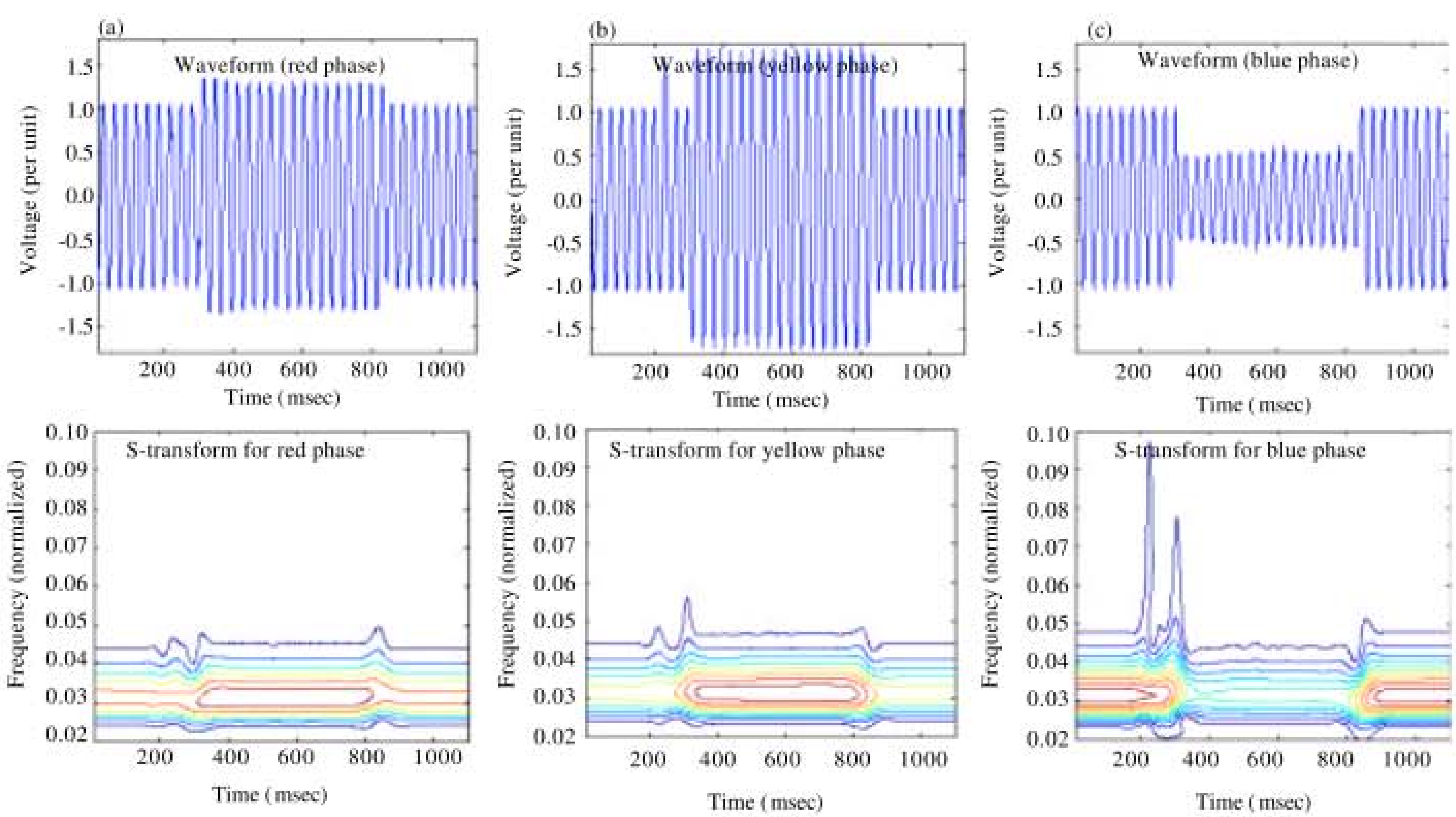

Fig. 12: S-transform contours for multiple disturbance, (a) swell, (b) swell and harmonic and (c) sag, harmonic and notch

successfully classified all the 7 numbers of disturbances. Figure 12, seven voltage disturbances, voltage swell (red phase), voltage swell and harmonics (yellow phase) and voltage sag, harmonic and notch (blue phase) were also successfully classified by the rule-based classifier. Figure 13, 14 and 15, eight, six and four disturbances were classified accordingly by the rule-based classifier.

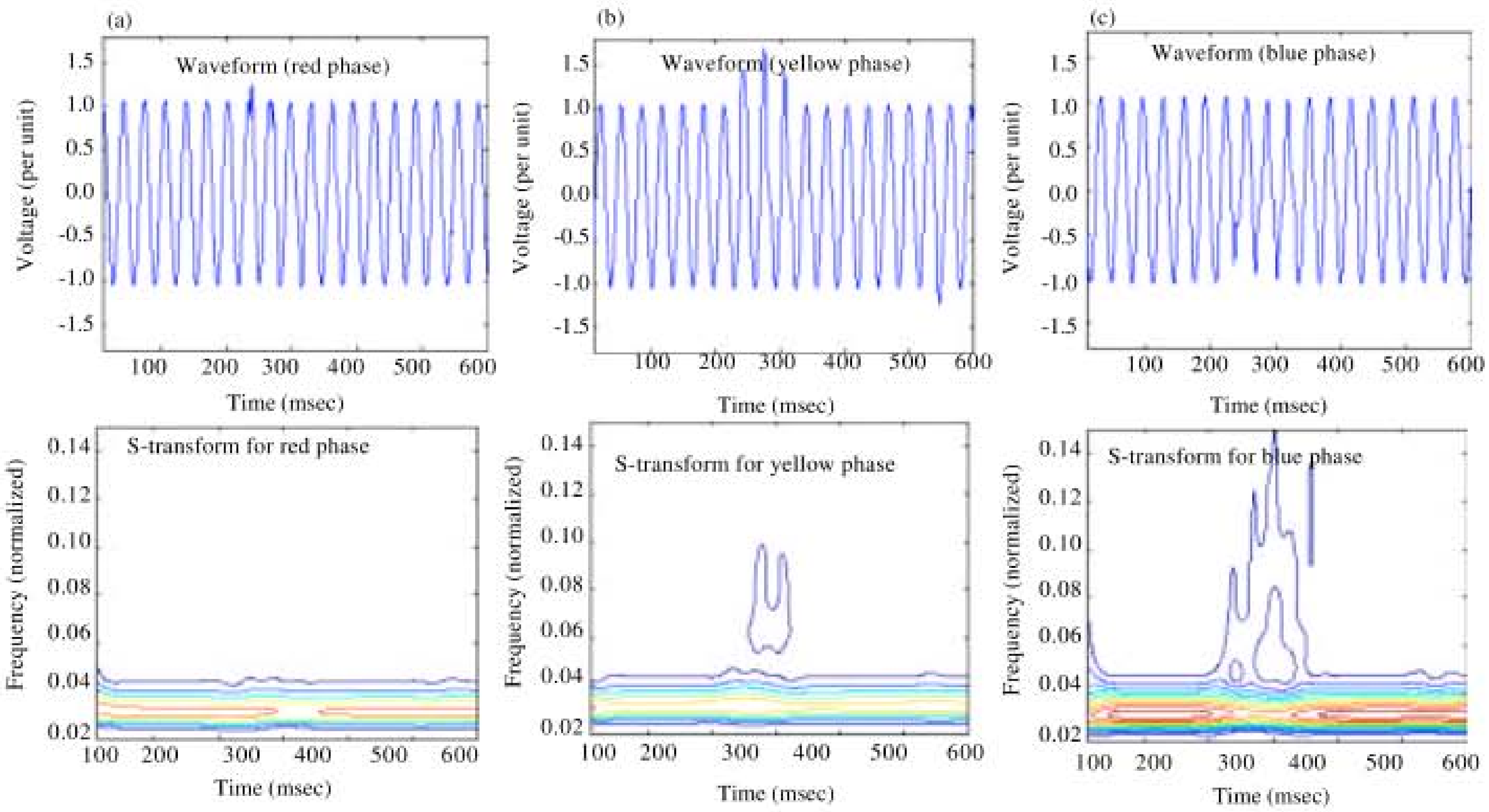

Fig. 13: S-transform contours for multiple disturbance, (a) harmonic and notch, (b) swell, notch and harmonic and (c) sag, harmonic and notches

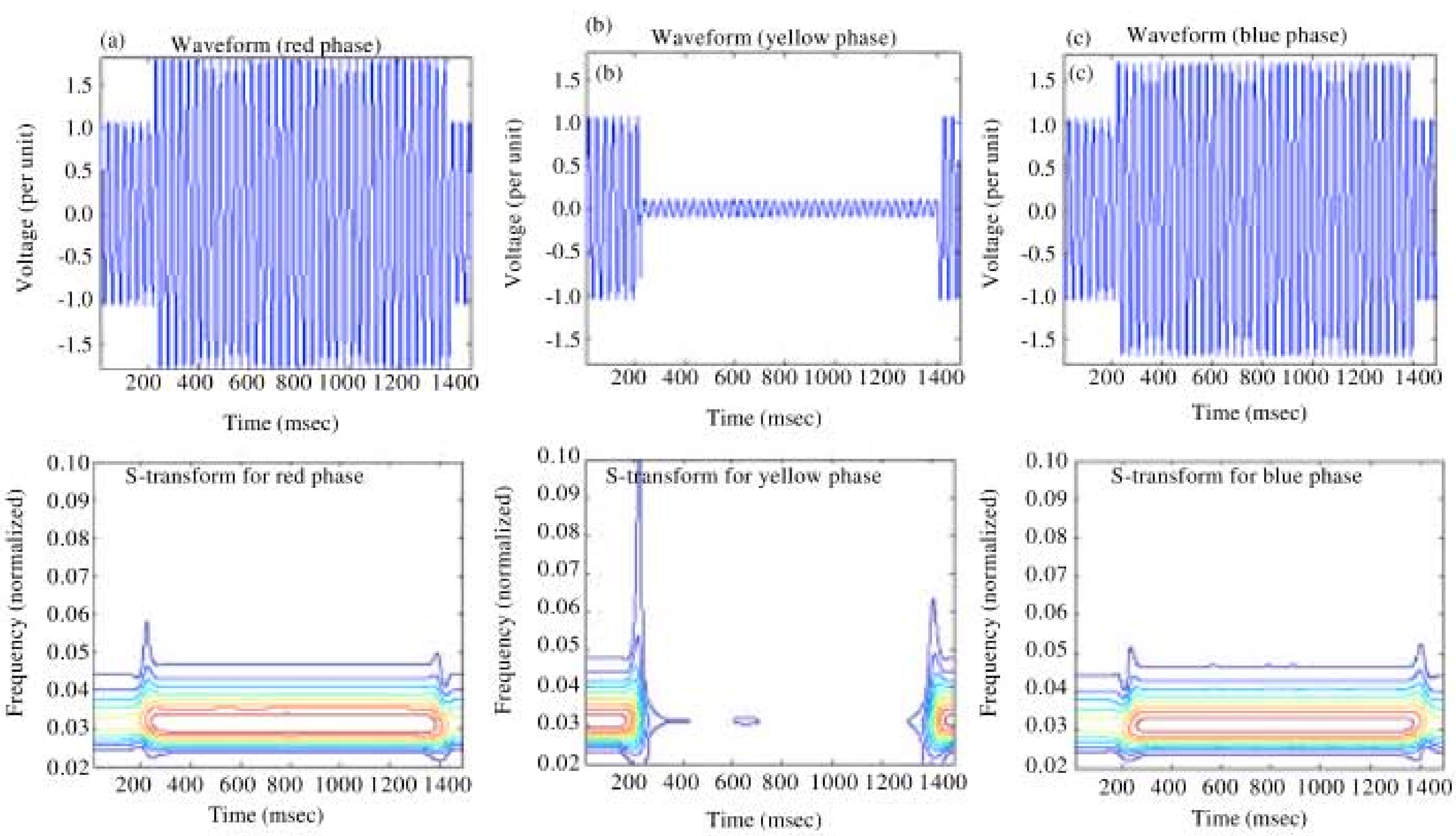

Fig. 14: S-transform contours for multiple disturbance, (a) swell and harmonic, (b) sag, harmonic and notch and (c) swell

Based on the results in Table 6 and 7, it was proven that the new technique is able to detect and classify both the single and multiple power quality disturbances. The supremacy of the S-transform is also noted for cases with noisy conditions. Some of the disturbances in this study have been recorded under noisy conditions and the S-transform can correctly detect the disturbances in both pure and noisy environment as shown in Fig. 13.

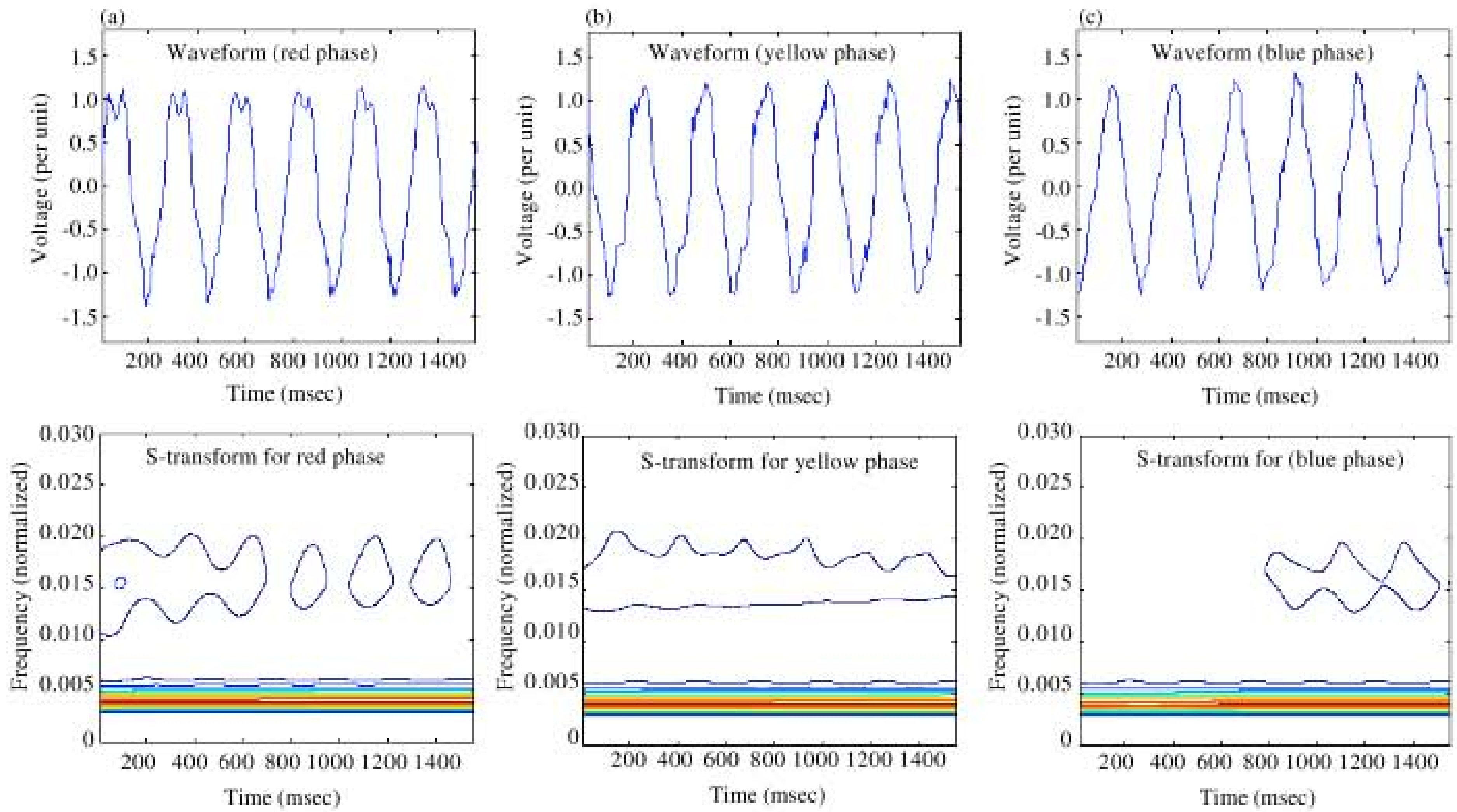

Fig. 15: S-transform contours for multiple disturbance, (a) harmonic, (b) harmonic and notch and (c) harmonic

And lastly, the features extraction developed in this study, has also given new insights on a future study to diagnose the sources and causes of the power quality disturbances.

CONCLUSION

In this study, a new technique to detect and classify single and multiple disturbances in electric signals is introduced. The main advantage offered by the technique is the use of the S-transform to decompose the powerline signals into a set of time-frequency components in which simple and powerful feature extraction and feature selection can be performed. The choice of the S-transform was made due to its characteristics that can uniquely combine a frequency dependent resolution that simultaneously localizes the real and imaginary spectra of the original waveforms. These features are then used by the rule-based classification technique to recognize the respective disturbance patterns in disturbance waveforms. The numerical results obtained with actual power quality data recorded in an industrial power system indicated that the new technique has perfect classification accuracy in the identification of both single and multiple disturbances. In future study, this new technique will be used for performing diagnosis on the sources and causes of the power quality disturbances.

REFERENCES

Bhende, C.N., S. Mishra and B.K. Panigrahi, 2008. Detection and classification of power quality disturbances using S-transform and modular neural network. Sci. Direct Elect. Power Syst. Res., 78: 122-128.

Bollen, M.H.J. and I.Y.H. Gu, 2006. Signal Processing of Power Quality Disturbances. IEEE Inc., John Wiley and Sons, Inc., USA, ISBN: 13-978-0-471-73168-9.

Bollen, M.H.J., I.Y.H. Gu, P.G.V. Axelberg and E. Styvaktakis, 2007. Classification of underlying causes of power quality disturbances: Deterministic versus statistical methods. EURASIP J. Adv. Signal Process., Vol. 2007, 10.1155/2007/79747.

Chilukuri, M.V. and P.K. Dash, 2004. Multiresolution S-transform-based fuzzy recognition system for power quality events. IEEE Trans. Power Delivery, 19: 323-330.

Chung, J., E.J. Powers, W.M. Grady and S.C. Bhatt, 2002. Power disturbance classifier using a rule-based method and wavelet packet-based hidden Markov model. IEEE Trans. Power Delivery, 17: 233-241.

Dugan, R.C., M.F. McGranaghan and H.W. Betty, 1996. Electrical Power Systems Quality. McGraw Hill Companies, London, ISBN: 0-07-018031-8.

Gargoom, A.M., N. Eetugrul and W.L. Soong, 2005. A Comparative Study on Effective Signal Processing Tools. EPE 2005, Dresden.

Godoy, R.B., J.O.P. Pinto and L.G. Junior, 2007. Multiple signal processing techniques based power quality disturbance detection, classification and diagnostic. Proceedings of the 6th International Conference, Oct. 9-11, Electrical Power Quality and Utilization, Barcelona, pp: 1-6.

Kennedy, B.W., 2000. Power Quality Primer. McGraw Hill Companies Inc., USA.

Negnevitsky, M., 2002. Artificial Intelligence: A Guide to Intelligent Systems. Addison Wesley, New York.

Polikar, R., 1994. The engineer's ultimate guide to wavelet analysis: The wavelet tutorial. http://users.rowan.edu /~polikar/WAVELETS/WTtutorial.html.

Reddy, J.B., D.K. Mohanta and B.M. Karan, 2004. Power system disturbance recognition using wavelet and S-transform techniques. Int. J. Emerg. Electric Power Syst., 1: 1-14.

Stockwell, R.G., L. Mansinha and R.P. Lowe, 1996. Localization of the complex spectrum: The S-transform. IEEE Trans. Signal Process., 44: 998-1001.

Styvaktakis, E., M.H.J. Bollen and I.Y.H. Gu, 2002. Expert system for classification and analysis of power system events. IEEE Trans. Power Delivery, 17: 423-428.