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DSP-FPGA BASED REAL-TIME POWER QUALITY DISTURBANCES CLASSIFIER

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Abstract

This paper describes a real-time classification method of power quality (PQ) disturbances based on DSP-FPGA. The proposed method simultaneously uses the results obtained in the application of a series of RMS values and the discrete Fourier transform to the power signal waveform. A series of RMS values are used for estimation of the time-related parameters of the PQ disturbances and the discrete Fourier transform is used for confirmation of the frequency-related parameters of the PQ disturbances. Without adding the computational burden, both the elementary parameters of the power signal and the type of PQ disturbance are obtained easily. A simple and effective methodology for classification of nine typical kinds of PQ disturbances is proposed in this paper. Five distinguished time-frequency statistical features of each type of PQ disturbances are extracted. Using a rule-based decision tree (RBDT), the PQ disturbances pattern can be recognized easily and there is no need to use other complicated classifiers. Finally, the method is also tested using both simulated disturbances and disturbances measured using an initial development instrument. Different experimental results show the good performance of this proposed approach. Real-time calculating time based on DSP is also taken into consideration to show the effectiveness of the proposed method.

Keywords: Discrete Fourier transform, power quality disturbances, real-time classifier, RMS, rule-based decision tree.

1. Introduction

Power Quality (PQ) has recently become a major concern to both electric suppliers and electric customers. One reason is that PQ has been being disturbed heavily with the increasing number of polluting loads (such as non-linear loads, time-variant loads, fluctuating loads, unbalanced loads, *etc*.), the other is that intelligent electrical devices have put forward more rigorous requirements for PQ. Therefore, PQ urgently needs to be monitored and improved. However, it is the key problem how to extract feature vectors automatically and classify PQ disturbances accurately from massive PQ data [1].

Several methods for detection and classification of PQ disturbances have been published. Some of them focus only on one particular type of disturbance [2], others aim to cover a wider range of disturbances [3, 4]. The wavelet transform is one of the most often employed signal processing algorithms [5–7]. It has been applied for detection of transients as well as sags or swells. However in the latter case it exhibits several drawbacks arising from weak response to sags and swells of a certain shape (especially when the voltage drops and increases are not sudden but gradual). In this paper, the features of each PQ disturbance are extracted from a series of RMS values and the discrete Fourier transform (DFT) to the power signal waveform.

The classification of PQ disturbances is often based on artificial neural network (ANN) [8], expert system (ES) [9] , fuzzy logic(FL) [10] , super vector machines (SVM) [11], a hidden

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Markov model (HMM) [12], and so on. In this paper, using a rule-based decision tree (RBDT) [13], the PQ disturbance pattern can be recognized easily and there is no need to use other complicated classifiers.

Most of PQ equipments that measure PQ indexes do record current and voltage RMS values, power values, power factor, frequency, harmonics from 2nd to 50th order and THD (Total Harmonic Distortion) [14, 15]. Unfortunately, due to the complex algorithm of the classification of PQ disturbances, it is a time-costly task for traditional equipment and must be implemented in a PC instead of the embedded device [16, 17].

The aim of this paper is to develop a real-time instrument that is suitable for automated real-time classification of PQ disturbances and the other functions. The emphasis is therefore on low computational burden required to perform the necessary calculations. In this paper, what is proposed in this work is the development of a method that can measure all elementary parameters of the power signal, plus the classification of PQ disturbances, which means all the functions of PQ analysis. A new method suitable for real-time detection and classification of various types of PQ disturbances are described. Special stress is laid on their suitability for the implementation in a DSP-FPGA-based measuring instrument. The method proposed in this paper does not add much of computational burden based on the traditional equipment, drastically improving the performance of the previous equipment and increasing the accuracy in the classification of PQ disturbances.

The paper is organized as follows. The feature extraction method is stated in Section 2. Then the design of RBDT is proposed in Section 3. Testing study results are presented in Section 4. At last, the conclusions are given in Section 5.

2. RMS and FFT based feature extraction

2.1. PQ disturbances

PQ disturbances that may occur in a power system can be extremely different in their characteristics. IEEE Std. 1159-1995 [1] describes categories of PQ disturbances and their typical characteristics. In this paper, the types of disturbances investigated are seven single disturbances and two complex disturbances, including the voltage sag, swell, interruption, harmonic, notch, flicker, oscillatory transient, sag with harmonics and swell with harmonics.

2.2. RMS and FFT based feature extraction

A good recognition system should depend on the features representing the PQ disturbances in such a way that the differences among the PQ disturbances' waveforms are suppressed for the waveforms of the same type but are emphasized for the waveforms belonging to different types of PQ disturbances. The following five distinct features inherent to different types of PQ disturbances have been extracted [3, 10, 18, 19].

*C*1: It represents the per unit (p.u.) RMS value of the fundamental component (50Hz power system).

$$V_n = \sqrt{2}abs(V^n[1]) / N, \tag{1}$$

where V_n is the RMS value of the fundamental component in the n-th cycle, N the number of samples in one cycle, n is the order number of the signal cycles, n = 1,2, ···, 10, $abs(\cdot)$ gives the absolute value of the argument, $V^{n}[k]$ is the DFT for the samples contained in the n-th cycle defined as:

$$V^n[k]=\sum_{i=0}^{N-1} v[i+(n-1)*N]e^{-j(2\pi ki)/N}, \tag{2}$$

where $v[i]$represents the sampled input signal, i = 0,1,2,⋯,L-1 with L the length of the signal. Assumed R_n is the rated RMS value of the normal signal, then the $C1$ is as following:

$$C1=\frac{V_n}{R_n}. \tag{3}$$

For example, to distinguish the interruption from the sag, the following rules are used: if $C1 \geq 1.1$, then the disturbance is swell; if $0.9 \geq C1 \geq 0.1$, then the disturbance is sag; if $C1 < 0.1$, then the disturbance is interruption; δ is the threshold used to distinguish notch from noise, $\delta \leq 0.01, C1 \leq 1-\delta$ for notch [20].

$C2$: It represents the variation rate of the RMS values of the power signal, which is defined as:

$$S_n = \left|V_{rms}^n - V_{rms}^{n-1}\right| / \Delta T, \tag{4}$$

where S_n is the alteration of two adjacent cycles of the RMS values, ΔT is the time interval, V_{rms}^n is the RMS value of the n-th cycle, which is defined as:

$$V_{rms}^n = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1} v^2[i+(n-1)*N]}. \tag{5}$$

Generally, there are two classes of PQ disturbances: stationary disturbances and non-stationary disturbances [1]. If $S > \varepsilon$, then the disturbance is non-stationary (sag, interruption, swell, oscillatory transient), then $C2$ = 1, for stationary (harmonic, notch, flicker) $C2$ = 0. ε is the threshold from noise, here $\varepsilon = 0.01$.

$C3$: It represents the oscillation number of the RMS variations of the power signal, which is defined as:

$$RN = root(V_{rms}^s - mean(V_{rms}^s)), \tag{6}$$

where RN is the oscillation number of the RMS variations, $root(\cdot)$ returns the number of roots of the argument, $mean(\cdot)$ returns the mean value of the argument, V_{rms}^s is defined as an array composed of V_{rms}^n .

$$V_{rms}^s = \left[V_{rms}^1 \; V_{rms}^2 \; \cdots \; V_{rms}^{10}\right]. \tag{7}$$

For example, to distinguish the flicker from the other disturbances if $RN \geq 3$, then $C3 = 1$, else $C3$ = 0.

$C4$: It represents the THD factor. If a disturbance happens, the frequency components will change greatly, and the additional frequency components derive from the disturbance. The THD in the n-th cycle is expressed as:

$$THD_n = \sqrt{\sum_{k=2}^{\mathrm{int}(N/2)} \left\{abs(V^{\mathrm{n}}[k])\right\}^2} \Big/ V^1[1], \tag{8}$$

where int(N/2) equals N/2 if N is even, and (N – 1)/2 if N odd. So, the following rule is used: if $THD_n \leq 0.05$ [7], then $C4$ = 0, else $C4$ = 1.

*C*5: It represents the LHD (lower harmonic distortion) factor. The LHD in the *n*-th cycle is expressed as:

$$LHD_n = \sqrt{\sum_{k=2}^{11} \{abs(V^n[k])\}^2} \Big/ V^1[1]. \tag{9}$$

For the three-phase power system, the most common harmonics are 5-th, 7-th and 11-th harmonics, which mean the lower frequency harmonics. Moreover, the frequency components associated with notch can be quite high [1]. Whereas the frequency components the following rule is used: if $LHD_n \geq THD_n - LHD_n$, then $C5 = 1$, else $C5 = 0$.

According to the above description and the PQ disturbances definition, the features of the nine types of disturbance are shown in Table 1, which can be the rules of identifying the PQ disturbance type.

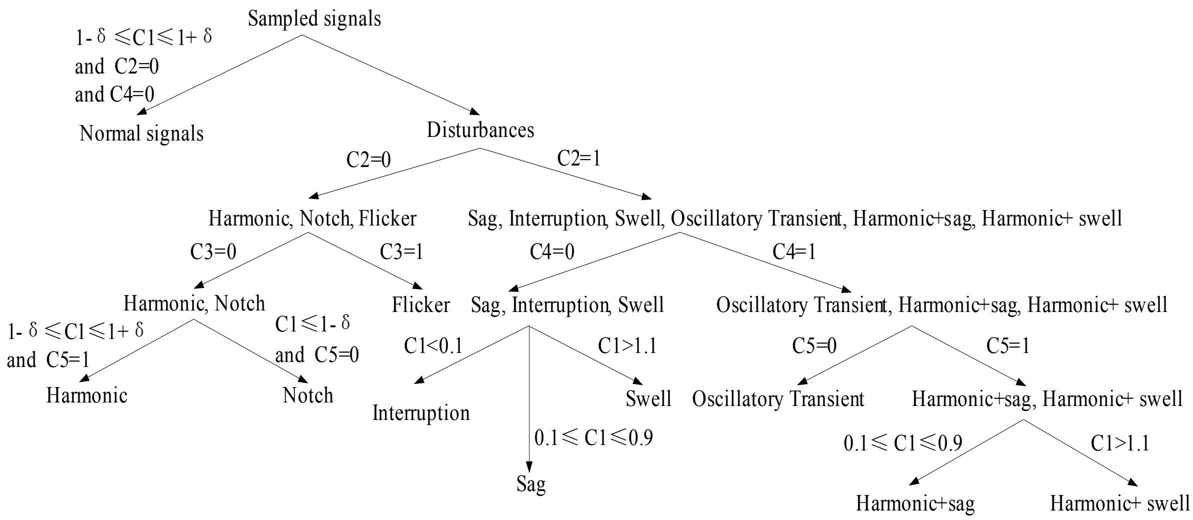


Fig. 1. Power quality classification tree.

Table 1. Disturbance signal features.

Type of signal	The values of features				
	C1	C2	C3	C4	C5
Normal signal	1	0	0	0	Not used
Sag	(≥0.1)&(≤0.9)	1	0	0	Not used
Interruption	≤0.1	1	0	0	Not used
Swell	(≥1.1)&(≤1.8)	1	0	0	Not used
Harmonic	(≥1-δ)&(≤1+δ)	0	0	1	1
Notch	≤1-δ	0	0	1	0
Flicker	Not used	0	1	Not used	Not used
Oscillatory transient	Not used	1	0	1	0
Harmonic + sag	(≥0.1)&(≤0.9)	1	0	1	1
Harmonic + swell	(≥1.1)&(≤1.8)	1	0	1	1

3. RBDT for Detection and Classification

According to Table 1, the disturbance classification tree is achieved, shown in Fig. 1. The decision tree is layered and based on a series of rules from Table 1. Using the decision tree, the above seven single disturbances and two complex disturbances can be recognized.

A decision tree is a tree data structure consisting of a root node, decision nodes and leaf nodes. A leaf identifies a class value. A decision tree classifies the type of the PQ disturbances by sorting them downwards the tree from the root to some particular leaf node, which identifies the PQ disturbance type. A decision node specifies a test over one of the features, which is called the feature (in our application we have five features, which describe the PQ disturbances) selected at the node, and each branch descending from that node corresponds to one of the possible values of the selected feature.

Each case is specified with values for a collection of features as described in the previous section. A divide-and-conquer strategy is used to construct the decision tree, wherein each leaf node in the tree is only associated with a set of features such as $C1, C2, C3, C4, C5$. So the decision tree model can be decided previously. Associated with each case is a label representing the name of a class. Classes are denoted by the names such as voltage sag, swell, interruption, harmonic, notch, flicker, oscillatory transient, sag with harmonics and swell with harmonics.

In Fig. 1, for a case, the decision tree makes comparisons at most 5 times (sag with harmonics and swell with harmonics), or at least 3 times (flicker), or on the average 4 times of comparison (sag, swell, interruption, harmonic, notch , flicker, oscillatory transient). So the expectation of the comparing times is as follows:

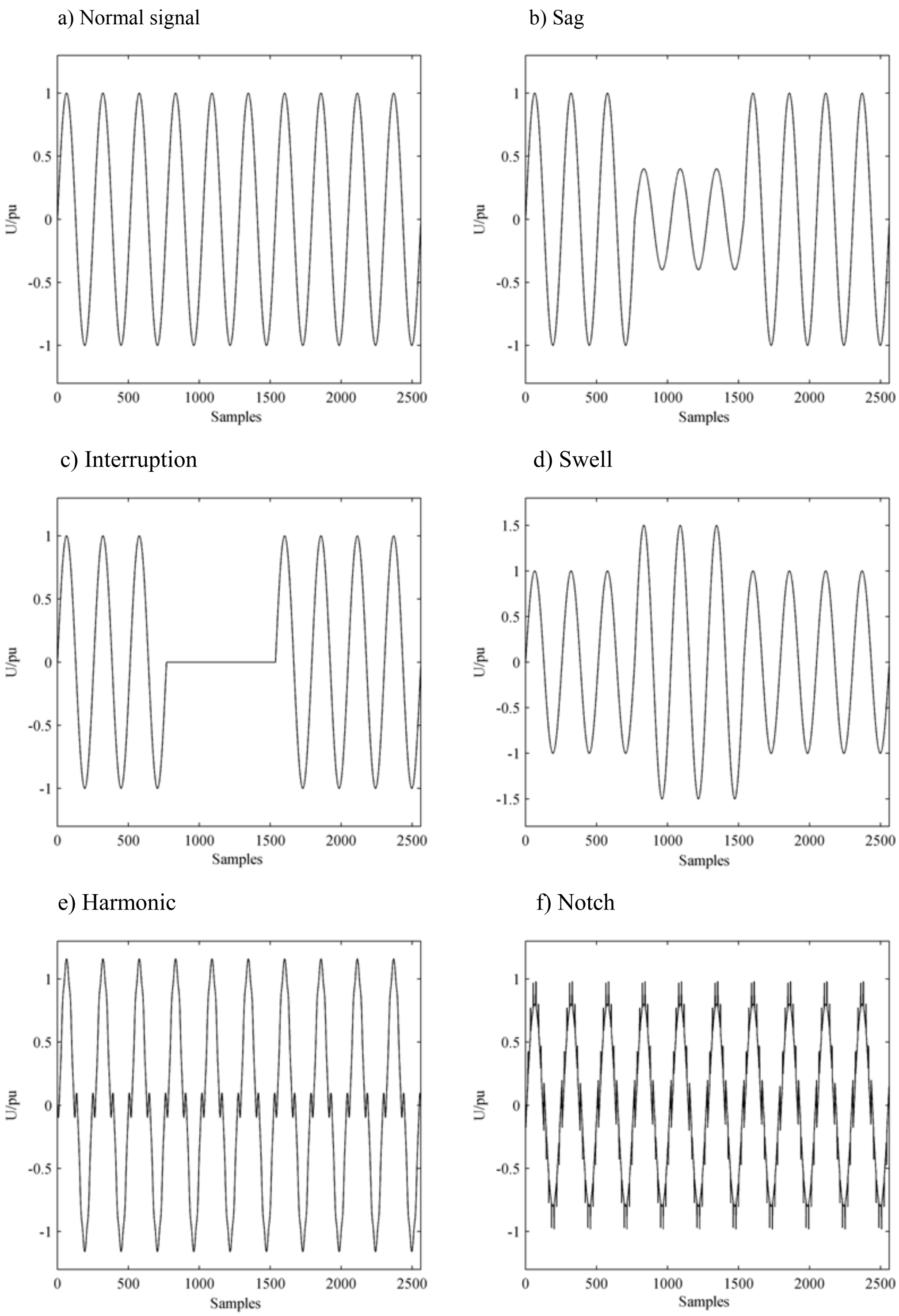
$$E = 5\frac{2}{9} + 4\frac{2}{3} + 3\frac{1}{9} = 4.11\,. \tag{10}$$

4. Tests and Discussion

In this section, the performance of the proposed method for detection and classification of PQ disturbances is evaluated first. The artificial PQ signals with disturbances are simulated using Matlab/Simulink programs. These disturbance waveforms are generated at a sampling rate of 256 samples/cycle for a total of 2560 points (10 cycles). In 100 cases of each disturbance, the program can be used to set different parameters such as the magnitude of the disturbance, its duration and its position within the period.

Fig. 2 shows the normal signal and above the nine types of power disturbance signals, respectively.

Each simulation lasts 10 cycles. In order to make values comparable for different cases, the amplitudes of the input signals have been normalized by dividing by the RMS value of the signal over the window being analyzed. All of the feature values are calculated on a sliding one-cycle window, which consists of 256 sampling points. The used features of PQ disturbances, which include $C1, C2, C3, C4, C5$, are grouped into the input vectors of RBDT. A Matlab program does all of the processing, and the classification results are presented in Table 2. Simulation experiments show that the performance of this classification system is satisfactory when there is Gaussian white noise with SNR (signal-to-noise ratio) from 30dB to 50dB. The average classification accuracy is 99%, 97.5%, 94% with SNR 50dB,40 dB, 30dB using the feature vectors that directly extract from the disturbance signal with noise, respectively. From Table 2, although the classification of PQ disturbances achieves above 90% accuracy averagely with SNR 30 dB, the identification of the sag and notch is sensitive to the noise, due to their same magnitude.


a) Normal signal
b) Sag
c) Interruption
d) Swell
e) Harmonic
f) Notch
U/pu
Samples

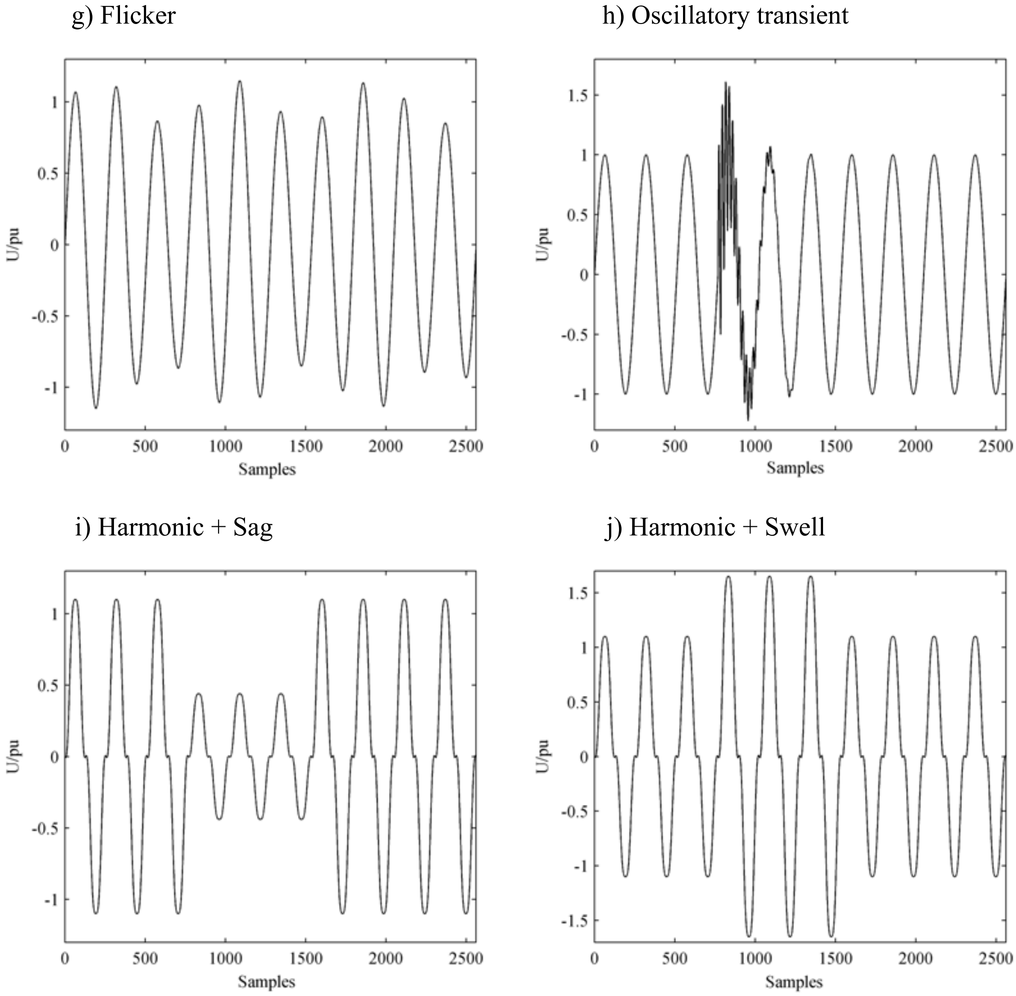


Fig. 2. PQ disturbance signals.

To evaluate the real-time performance of the proposed method, the hardware experiment has contributed to the initial design of a universal power quality test bench, which has the function of classifying PQ disturbances.

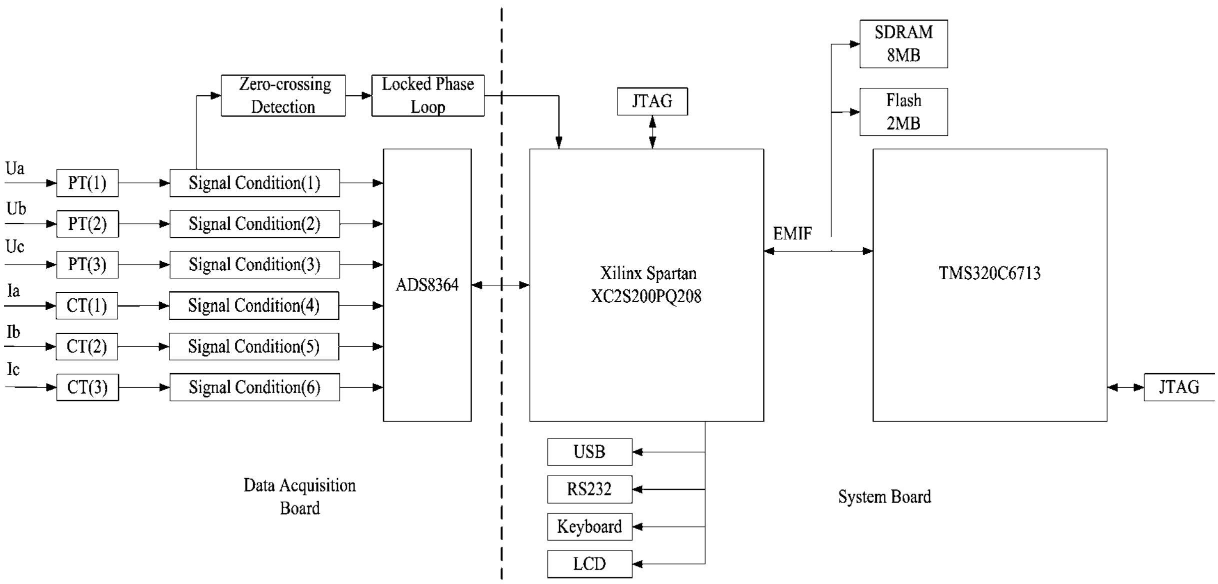


Fig. 3. Block diagram of hardware configuration.

A simplified block diagram of hardware configuration is shown in Fig. 3. This device applies DSP and FPGA and a simple peripheral circuit to realize the function of signal acquisition, processing and display. Fig. 4 shows the flow chart of the software.

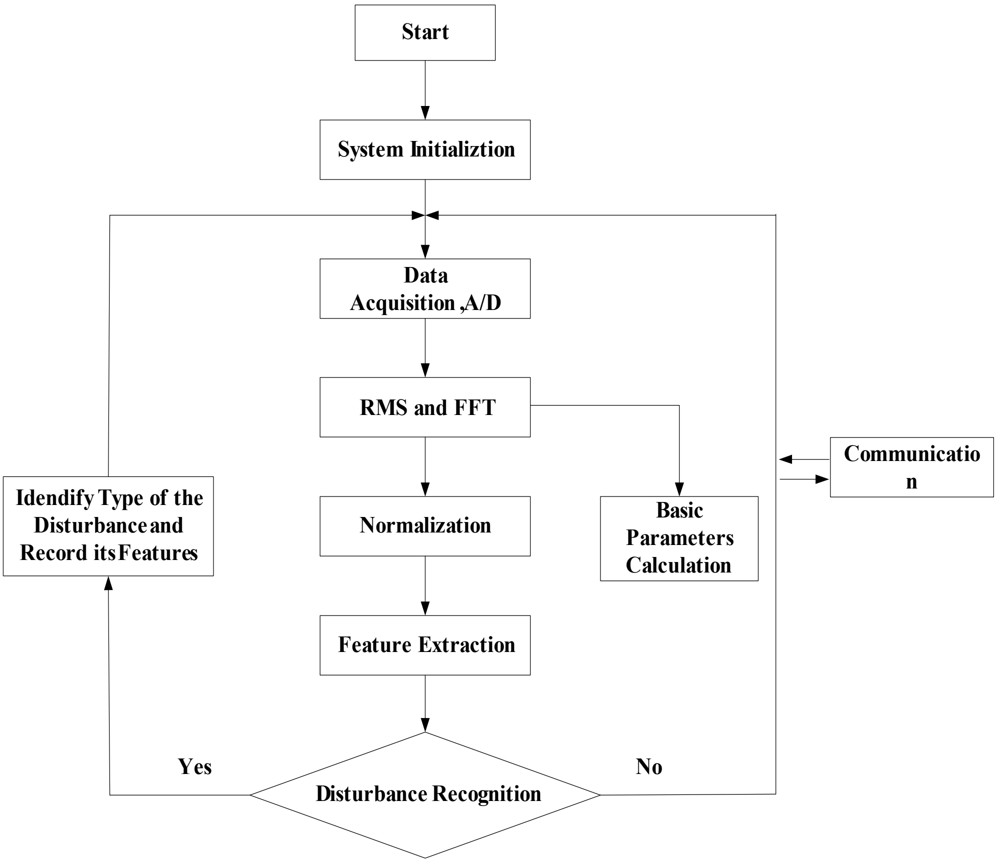


Fig. 4. Flow chart of the software.

To implement the proposed method in the hardware device, both classification accuracy and real-time requirements need to be considered. Each type of PQ disturbances generated by the Fluke 61000A is tested 20 times at a sampling rate of 256 samples/cycle for a total of 2560 points (10 cycles). Fig. 5 shows the connection of the test devices.

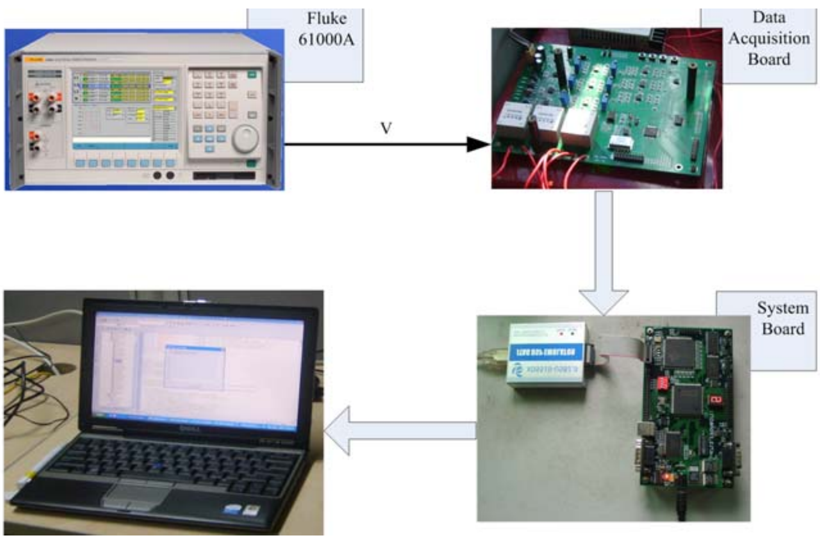
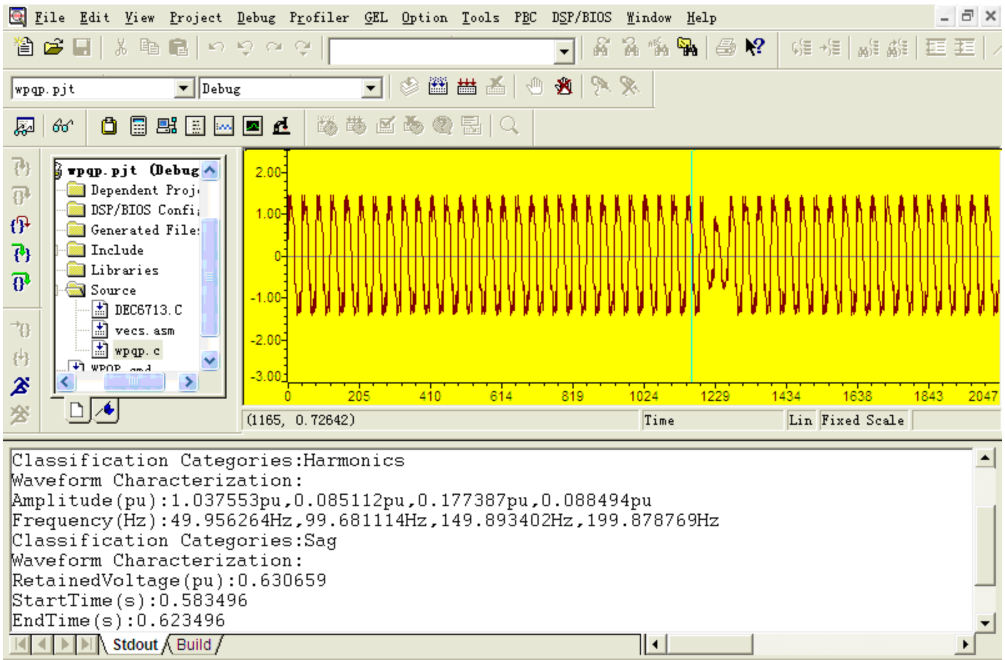


Fig. 5. Connection of the test devices.

Fig. 6 shows two test cases of the classification of PQ disturbances in the device. Fig. 7 shows the consuming time of DSP for the classification of the various types of PQ disturbances from 0.09s to 0.12s on the average. From Table 2 and Fig. 7, test results show that the proposed method achieves acceptable classification accuracy and meets the real-time requirements of real applications

a) Sag + harmonic disturbance



b) Swell disturbance

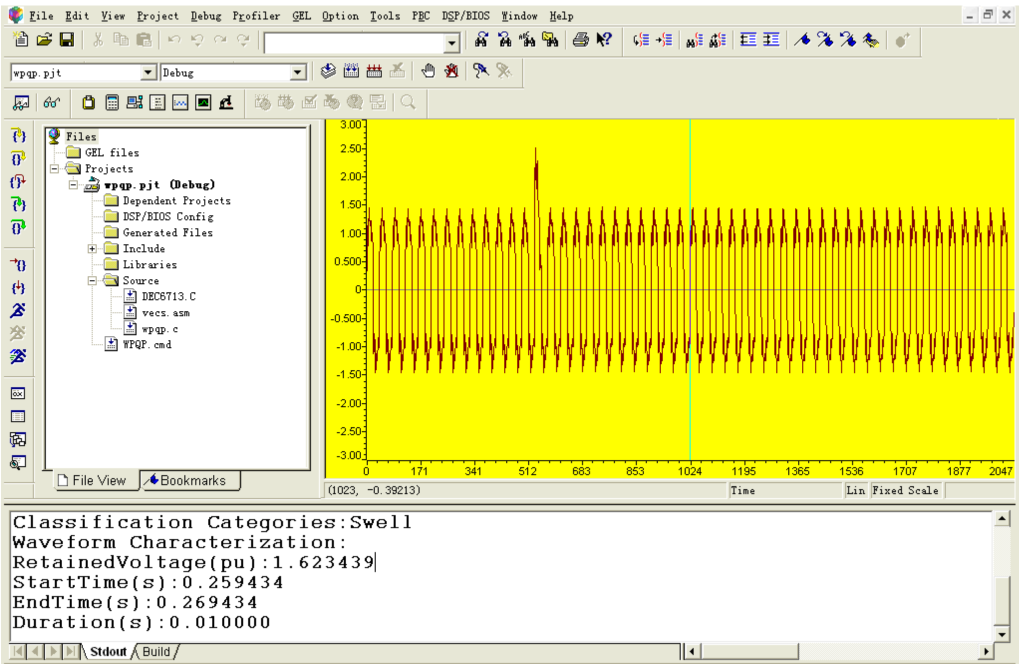


Fig. 6. Test cases of classification.

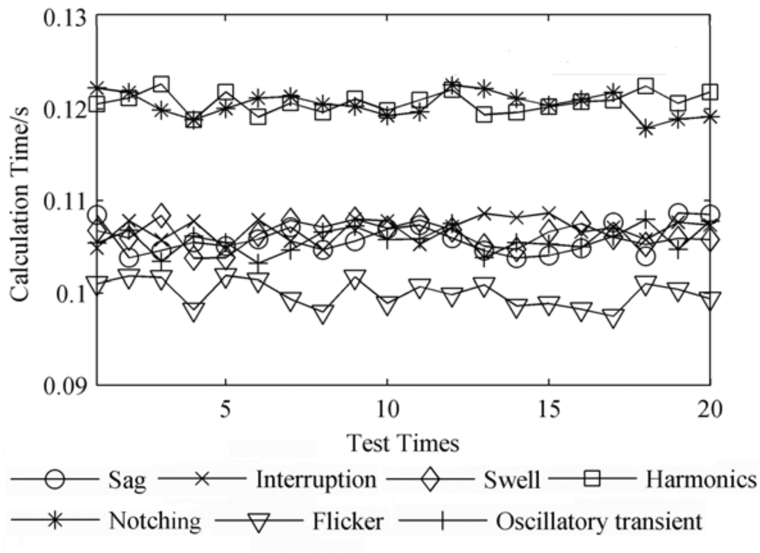


Fig. 7. Consuming time of DSP.

5. Conclusions

A novel method for detection and classification of PQ disturbances has been developed. The method detects voltage sag, swell, interruption, harmonic, notch , flicker, oscillatory transient, sag with harmonics and swell with harmonics. The initial stages of development of a power quality instrument are also described in this paper. Compared to common solutions which are usually based on wavelet transform, the proposed method is faster, simpler and more suitable for real-time monitoring of power systems. The proposed method is tested using simulated signals with disturbances and using measured signals gathered from a Fluke 61000A instrument. Test results show that the proposed method achieves acceptable classification accuracy and meets the real-time requirements.

Table 2 Tests of disturbance classification.

Type of signal	SNR50dB		SNR 40dB		SNR 30dB	
	Samples	Misestimate times	Samples	Misestimate times	Samples	Misestimate times
Sag	100	0	100	1	100	4
Interruption	100	0	100	5	100	13
Swell	100	0	100	1	100	4
Harmonic	100	0	100	0	100	1
Notch	100	2	100	6	100	14
Flicker	100	3	100	4	100	5
Oscillatory transient	100	4	100	4	100	6
Harmonic+sag	100	0	100	1	100	4
Harmonic+ swell	100	0	100	1	100	3
Mean accuracy (%)	99		97.5		94	

Acknowledgements

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