DSP-FPGA Based Real-time Power Quality Disturbances Classifier

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Abstract—**This paper describes an 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.**

Index Terms—**Discrete Fourier transform, power quality disturbances, real-time classifier, RMS, rule-based decision tree**

I. 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 that 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] ,and hidden 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 the traditional equipments, and must be implement in PC instead of in 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 an method that can measure all elementary parameters of the power signal, plus the classification of PQ disturbances, which means all the function 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 proposed method in this paper does not add much of computational burden based on the traditional equipments, drastically improving the performance of the previous equipments and increasing the accuracy in the classification of PQ disturbances.

The paper is organized as follows. The feature extraction method is stated in Section II. Then the design of RBDT is proposed in Section III. Testing study results are presented in Section IV. At last, the conclusions are given in Section V.

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II. RMS AND FFT BASED FEATURE EXTRACTION

A. 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 are seven single disturbances and two complex disturbances, including the voltage sag, swell, interruption, harmonic, Notching, flicker, oscillatory transient, sag with harmonics, and swell with harmonics.

B. 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 of 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].

$C1$: It represents the per unit (p.u.) RMS value of the fundamental component (50Hz).

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

where V_n is the RMS value of the fundamental component, N the number of samples in one cycle, n is the order number of the signal cycles, $n = 1, 2, \cdots, 10$, a$bs(\cdot)$ gives the absolute value of the argument, $V^n[k]$ is the DFT for the samples contained in the nth cycle defined as

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

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

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

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 Notching from noises, $\delta \leq 0.01$, $C1 \leq 1 - \delta$ for Notching [20].

$C2$: It represents the variation rate of the RMS values.

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

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 shown 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 stationary (sag, interruption, swell, oscillatory transient), then $C2 = 1$, for stationary (harmonic, Notching, flicker) $C2 = 0$. ε is the threshold from noises, here $\varepsilon = 0.01$.

$C3$: It represents zero-crossing number of the RMS values.

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

where RN is the zero-crossing number of the RMS values, 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 total harmonic distortion. If the disturbance happens, the frequency components will change greatly, and the additional frequency components derive from the disturbance.

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

where THD_n is total harmonic distortion, 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 $C4 = 1$.

$C5$: It represents lower harmonic distortion.

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

where TS_n is lower harmonic distortion. 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 Notching can be quite high [1]. Whereas the frequency components of the oscillatory transient are usually high frequency. So, the following rule is used: If $TS_n \geq THD_n - TS_n$, then $C5 = 1$, else $C5 = 0$.

TABLE I
DISTURBANCE SIGNAL FEATURES

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