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Power quality disturbances analysis based on EDMRA method

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ABSTRACT

An Energy Difference of Multiresolution Analysis (EDMRA) method for power quality (PQ) disturbances analysis has been proposed in this paper. At each wavelet decomposition level, the squared value of the detail information is calculated as their energy to construct the feature vector for analysis. Following the criteria proposed in this paper, different kinds of power quality disturbances can be detected, localized, and classified effectively. The choice of the decomposition levels of appropriate wavelets are of the critical importance for the EDMRA method, since they will influence quality of the reconstructed signal as well as the computational cost. It is presented in this paper that the Minimum Decomposition Level (MDL) is related to the sampling frequency by the proposed function. The comparison study among different kinds of wavelets for the EDMRA method is presented in details. The EDMRA method is scalable and has robustness characteristics in common design paradigm. It can be realized economically using wavelets with shortest length, such as Harr, Db2, Sym2 or Coif 1. Two types of noise, namely, Gaussian white noise and band limited spectrum noise are considered in this paper to show the effectiveness of the proposed method in noisy environment.

1. Introduction

This paper aims to develop an effective method for power quality (PQ) disturbances detection, localization and classification. With the fast expansion of power electronics and other nonlinear, time-variant loads in the power distribution network, power quality has become a critical issue and attracted growing attention in power industry and academic. For example, according to the survey by IEEE Transactions on Industrial Applications (IAS) for 210 large commercial and industrial customers, the average cost for a 4-h outage and a momentary outage are $74,835 and $11,027, respectively [1]. Also, according to the data investigated by Electrical Power Research Institute (EPRI), the US economy is losing between $104 billion and $164 billion a year to outages, and another $15 billion to $24 billion for PQ phenomena [2]. For instance, the power outage in North America in August, 14, 2003 influenced the vast area from east of New York, north to Toronto and west to Detroit, Michigan – an area that is home to about 50 million people. It leads to losses of $4 billions to $10 billions in the USA alone [3]. Therefore, the research of power quality issues has captured ever increasing attention in the power engineering society.

Recent advances in the wavelet transforms provide a powerful tool for power quality analysis. In the wavelet based PQ analysis, there are two major categories of techniques. The first one is the wavelet based data compression for power quality disturbances. For instance, Hamid and Kawasaki proposed the power quality disturbances data compression techniques via discrete wavelet transform and wavelet packet transform [4]. In [5], compression techniques using spline wavelet are performed through signal decomposition, thresholding of wavelet coefficients, and signal reconstructions. A modified wavelet transform, known as S-transform, has been used for such analysis. Panda et al. used the Slantlet Transform (SLT) for data compression of power quality events [6]. The SLT can design different filters for different scales unlike iterated filter bank approaches for conventional discrete wavelet transform (DWT). The second category is the wavelet based detection, localization, and classification of the power quality problems. For instance, Poisson et al. presented a good comparison among the continuous wavelet transform, the multiresolution analysis (MRA) and the quadratic transform for power quality analysis [7]. The same authors proposed a recursive algorithm based on continuous wavelet transform to detect and analyze voltage sags and transients [8]. The comparison between measured characteristics and benchmark values are used to detect the presence of disturbances in analyzed signals and characterize the type of disturbances. Santoso et al. presented the characterization analysis of distribution power quality events with Fourier and Wavelet Transform

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[9]. S-transform is used in [10] for detecting, localizing, and classifying PQ problems. Wavelet based online disturbance detection for power quality applications are discussed in details in [11,12]. For the type of transient event, it has been shown that the method has advantages of being faster and more precise in discrimination than conventional approaches. A two-stage system that employs the wavelet transform and the adaptive neuro fuzzy networks for power quality identification is proposed in [13]. In this method, the wavelet multiresolution signal analysis is exploited to reduce noise and then decompose the monitored signals of the power quality events to extract its detailed information. A new optimal feature-vector is suggested and adopted in learning the neurofuzzy classifier. Gaouda et al. proposed an effective wavelet multiresolution signal decomposition method for analyzing the power quality transient events in [14,15]. Several typical power quality disturbances were correctly localized and classified. Santoso et al. utilized the squared wavelet transform coefficients to detect and localize the PQ disturbances in [16]. Liao and Lee proposed a fuzzy-expert system for automated detection and classification of power quality disturbances, in which wavelet transform was used to obtain the features for the analyzed signal [17]. Since the signal under investigation is often corrupted by noise, a de-noising scheme for enhancing wavelet based power quality monitoring systems is presented in [18]. In this scheme, the threshold for eliminating the noise influence is processed adaptively according to the background noise. Recently, a self organizing learning array (SOLAR) system based on wavelet transform is proposed for power quality disturbances classification [19]. Comparison research of this method with support vector machine (SVM) method on several typical PQ disturbance classifications shows that the proposed method can provide accurate classification results [19].

Although lots of research achievements have been reported in recent literature, the objective of detecting, localizing and classifying different kinds of power quality disturbances is still both challenging and time-consuming. This paper aims to develop a novel wavelet based scheme for PQ problems – Energy Difference of Multiresolution Analysis (EDMRA). The rest of this paper is organized as follows. In Section 2, a brief description of the wavelet transform and MRA is presented. Section 3 discusses in detail the proposed EDMRA method. Wavelet MRA is used to decompose the sampled waveform to several levels. At each decomposition level, the energy (squared value) of the detail information is used to construct the feature vector for analysis instead of the standard deviation [14] and the root mean square value [15]. The advantages of this method are lower computational cost and better anti-noise performance. To avoid unnecessary computation cost, an efficient approach to find the Minimum Decomposition Level (MDL) for the EDMRA method is discussed in detail in this section. Since different wavelets have different characteristics and different computational cost, the selection of appropriate wavelets is also discussed in this section. Section 4 discusses the performance of the EDMRA method in different noisy environments. Gaussian white noise and band limited spectrum noise are taken into account for analysis and Monte-Carlo methods are used. Finally, a conclusion is given in Section 5.

2. Wavelet transform and MRA

Mathematics of the wavelet transform was extensively studied and can be referred in [20,21]. Unlike the Short Time Fourier Transform (STFT) with a fixed window function, the wavelet transform involves a varied time–frequency window and can provide good localization property in both time and frequency domain, which yields nice performance in analyzing PQ disturbances. Fig. 1a and b gives the time–frequency characteristic of STFT and wavelet transform, respectively [7]. From Fig. 1a we can see, that the STFT has a fixed time–frequency window (Δt and Δf), which means it is lacking flexibility. However, the wavelet transform can provide varied time–frequency windows at different scales (Fig. 1b). This enables users to choose a proper window to see signals at different resolutions. This is the main advantages of wavelet transforms comparing with the STFT.

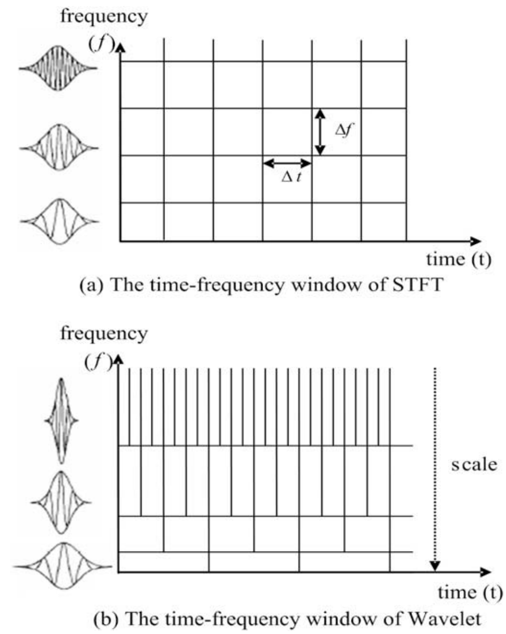

Fig. 1. Time–frequency characteristics of STFT and Wavelet [7].

The MRA was introduced by Mallat in [22]. Define V_j, $j \in Z(integers)$ as a sequence of linear subspaces. The MRA can be described through a nested subspaces spanned by a single scaling function ϕ together with its translates and dilates $\phi(2^m t - k)$,

$$\cdots \subset V_{-2} \subset V_{-1} \subset V_0 \subset V_1 \subset V_2 \subset \cdots \subset L^2 \tag{1}$$

or $V_j \subset V_{j+1}$ for all $j \in Z$ and $\overline{\cup_j V_j} = L^2$ and $\cap_j V_j = \{0\}$.

From Eq. (1) we can see that, as j goes to infinity, V_j enlarges to become all energy signals (L^2), as j goes to negative infinity, V_j shrinks down to only zero.

For every $j \in Z$, define W_j to be the orthogonal complement of V_j in V_{j+1}, then

$$V_{j+1} = V_j \oplus W_j \quad \text{and} \quad W_j \perp W_{j'} \quad \text{if } j \neq j'. \tag{2}$$

The above Eqs. (1) and (2) can be visualized in Fig. 2. In MRA, any time series $x(t)$ can be completely decomposed in terms of the approximations, provided by scaling functions $\phi_{m,n}(t)$ and the details, provided by the wavelets $\psi_{m,n}(t)$, where

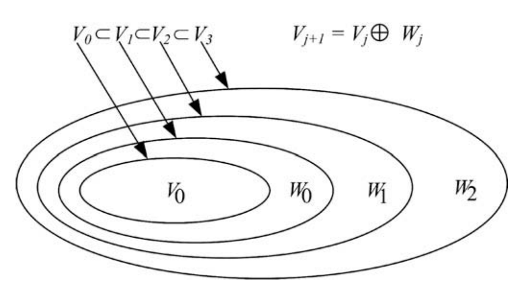

Fig. 2. Nested subspaces of MRA.

$$\phi_{m,n}(t) = 2^{-m/2}\phi(2^m t - n), \tag{3}$$
$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^m t - n). \tag{4}$$

The approximations are the low-frequency components of the time series and the details are the high-frequency components. MRA leads to a hierarchical fast scheme. This can be implemented by a set of successive filter banks as described in [20]. In this way, the decomposition of signal $x(t)$ can be expressed as

$$\begin{aligned} x(t) &= A_1(t) + D_1(t) \\ &= A_2(t) + D_2(t) + D_1(t) \\ &= A_3(t) + D_3(t) + D_2(t) + D_1(t) \\ &= \cdots \end{aligned} \tag{5}$$

where $A_m(t) = \sum_{n=-\infty}^{m} a_{mn}\phi_{mn}(t)$, and $D_m(t) = \sum_{k=0}^{m}\sum_{n=-\infty}^{\infty} b_{kn}\psi_{kn}(t)$, are called the approximation and detail at level m, respectively. $a_{nm} = \int_{-\infty}^{\infty} f(t)\phi_{mn}(t)dt$ and $b_{mn} = \int_{-\infty}^{\infty} f(t)\psi_{mn}(t)dt$ are called scaling and wavelet coefficients, respectively.

3. The proposed EDMRA approach: method, performance and cost

3.1. Energy difference of MRA (EDMRA) method

From the above analysis we can see, the characteristics of the original waveform can be reflected in different scales after the MRA decomposition. Based on this observation, we can construct the feature vector to detect different kinds of PQ disturbances. This idea is shown in Fig. 3. The sampled waveform was decomposed into different resolution levels (i) according to MRA. Then the energy of the detail information at each decomposition level i is calculated according to the following equation:

$$E_i = \sum_{j=1}^{N} |D_{ij}|^2, \quad i = 1, \ldots, l \tag{6}$$

where $D_{ij} = b_{ij}$, $i = 1, \ldots, l$ is the wavelet (detail) coefficients in wavelet decomposition from level 1 to level l. N is the total number of the coefficients at each decomposition level and E_i is the energy of the detail at decomposition level i. In order to identify different kinds of PQ disturbances, the energy difference (ED) at each decomposition level is calculated, which is the difference of the energy E_i with the corresponding energy of the reference (normal) waveform at this level $E_{ref(i)}$,

$$ED_i = E_i - E_{ref(i)} \tag{7}$$

By observing this ED_i feature vector at different resolution levels and following the criterion proposed later in this section, one can effectively detect, localize and classify different kinds of PQ disturbances. This method is named as Energy Difference of MRA (EDMRA) method. The major advantages of this method include two aspects. The first one is that by using this method, one can significantly reduce the dimensionality of the analyzed data. As we can see from Fig. 3, for a l levels multiresolution decomposition, only a l-dimensional feature vector need to be observed. This is a significant reduction compared to the original sampled waveform. The second advantage is that this method keeps all the necessary characteristics of the original waveform for analysis. Different PQ characteristics are represented by the energy difference at different resolution scale, which provides an effective way for different types of PQ detection.

Fig. 4 shows a normal pure sine wave (60 Hz) and its four types of typical PQ disturbances: low frequency distortion, high frequency distortion, voltage sag and voltage swell. Sampling frequency used is 5 kHz. These PQ disturbance models are based on the IEEE Standard 1159-1995 (IEEE Recommended Practice for Monitoring Electric Power Quality) [26], which are widely adopted in the academic and industry community [15,19]. Specifically, for the short duration variations, the typical duration for voltage sag is from 0.5 to 30 cycles with the voltage magnitude between 0.1 and 0.9 pu, while the typical duration for voltage swell is from 0.5 to 30 cycles with the voltage magnitude between 1.1 and 1.8 pu. For the frequency distortions, the typical spectral content for low frequency distortion is less than 5 KHz with the voltage magnitude of 0–4 pu, while for the high frequency distortions, the typical spectral content is between 0.5 and 5 MHz with the voltage magnitude of 0–4 pu. A detailed discussion of these typical PQ characteristics can be found in [26] and detailed mathematical models can also be found in [19]. In our current study, we use the Daubechies 4 (Db4) wavelets and 12 levels decomposition for analysis. Since it is well known that wavelet transform can localize the time information for PQ disturbances, we will focus on the characteristics analysis and performance evaluation of the proposed EDMRA method. Interested audiences can refer to paper [14,18] for the detection of the beginning and ending time of the power quality disturbance. Fig. 5 give the EDMRA analysis result to the signals in Fig. 4a–d, where the horizontal axis represents the decomposition level (scale) and the vertical axis is the energy difference as defined in Eq. (7).

Based on the analysis result in Fig. 5, the following criteria are proposed for detecting and classifying different kinds of PQ disturbances.

Conjecture 1:

(1) If the peak-value of the ED is located at scale 6 (curve c and d), it is an amplitude distortion, which means either swell or sag disturbance. Otherwise, it is a frequency distortion.
(2) If the triangle (peak-value) is concave downward (curve d, negative ED), the distortion is a swell. If the triangle is concave upward (curve c, positive ED), the distortion is a sag.

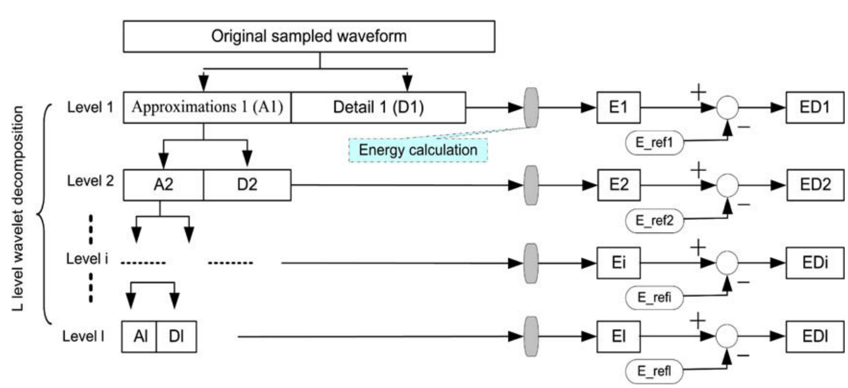

Fig. 3. EDMRA system architecture.

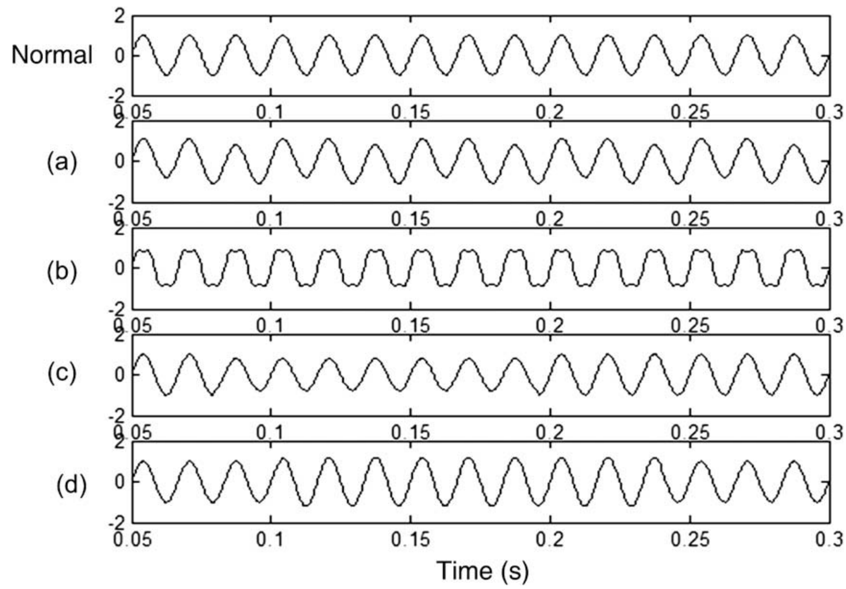

Fig. 4. Original normal waveform and its distortion signal. (a) Low frequency distortion; (b) high frequency distortion; (c) voltage sag from 0.08 s to 0.196 s; (d) voltage swell from 0.104 s to 0.24 s.

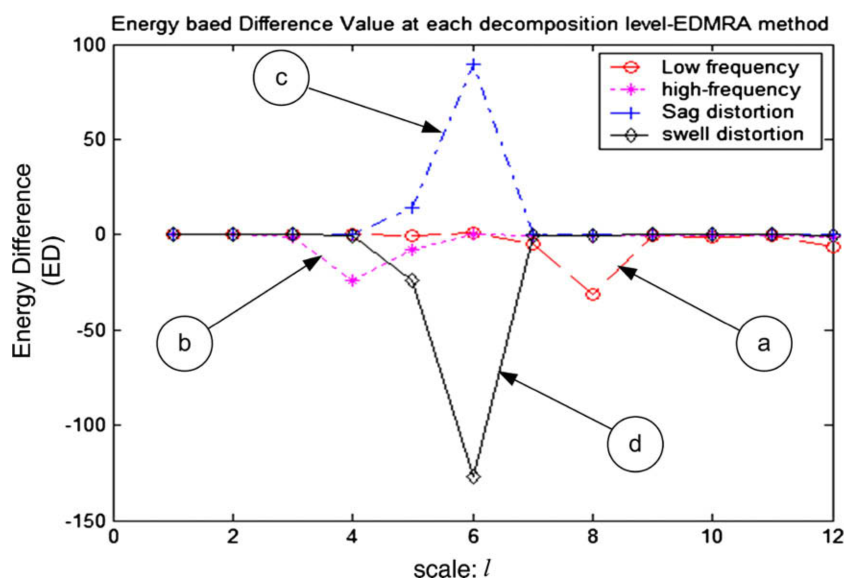

Fig. 5. EDMRA analysis result for the signal in Fig 4.

(3) If the peak-value is at scale smaller than 6 (curve b), it is a high-frequency disturbance.
(4) If the peak-value is at scale higher than 6 (curve a), it is a low-frequency disturbance.

One thing should be noted here is that the reference scale 6 is related to the sample frequency f_s and normal frequency of the power signal (50 Hz or 60 Hz), this will be discussed in detail in Section 3.3.

3.2. Study of Joint impact of the frequency distortion and amplitude distortion

In the above Section 3.1, we consider the frequency distortion and amplitude distortion separately. In practical electrical distribution network, the distorted signal may contain both of these two kinds of distortions. In this part, we study the joint impact of these two distortions for the proposed EDMRA method.

Fig. 6 shows the joint impact of the frequency and amplitude distortions. The upper part of Fig. 6 is the signal sag during 0.08–0.196 s combined with a low frequency distortion. The lower part of Fig. 6 is the signal swell during 0.104–0.24 s with a high frequency distortion. To illustrate the effectiveness of the wavelet transform for detection of the beginning and ending time of the sag and swell in this situation, we use the first level detail information of the wavelet decomposition to localize the time information. Fig. 7 shows the analysis results and we can see the beginning and ending time of the sag and swell are effectively detected in this case.

Fig. 8 shows the analysis results for the proposed EDMRA method with wavelet decomposition at level 12. Comparing Figs. 8 and 5, we conclude that the EDMAR method still maintains all the

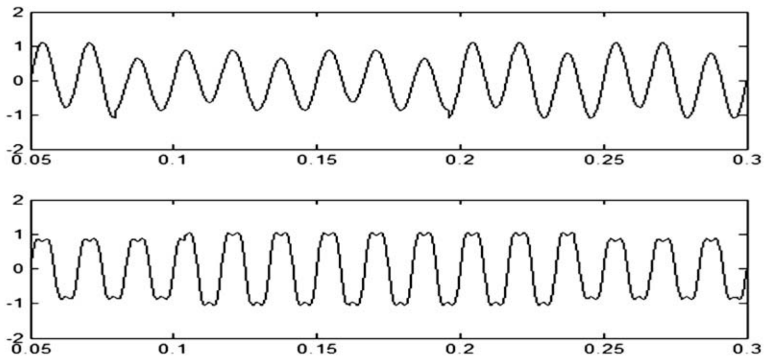

Fig. 6. Joint impact of the frequency distortion and amplitude distortion.

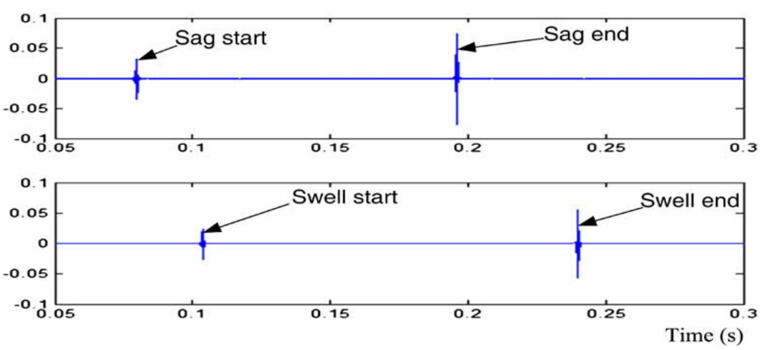

Fig. 7. First level detail information of the signal in Fig. 6.

characteristic points to correctly classify different kinds of PQ disturbances. Based on the justification criteria proposed in this paper, we can say that curve 1 represents the sag in a low frequency distortion and curve 2 is the swell in a high frequency distortion.

3.3. Determination of the MDL

Using the methodology presented so far, we can detect, localize and classify different kinds of PQ disturbances based on the EDMRA method. However, how many levels of decomposition are enough for the EDMRA method to be effective? Obviously, more levels of decomposition will increase the computational cost. In this part, we aim to find the Minimum Decomposition Level (MDL) for the proposed method and modify the above evaluation criterions to be universal.

In MRA, since both the high pass filter and the low pass filter are half band, the decomposition in frequency domain for a signal sampled with the sample frequency f_s can be demonstrated in Fig. 9. Assuming the total decomposition levels for EDMRA method

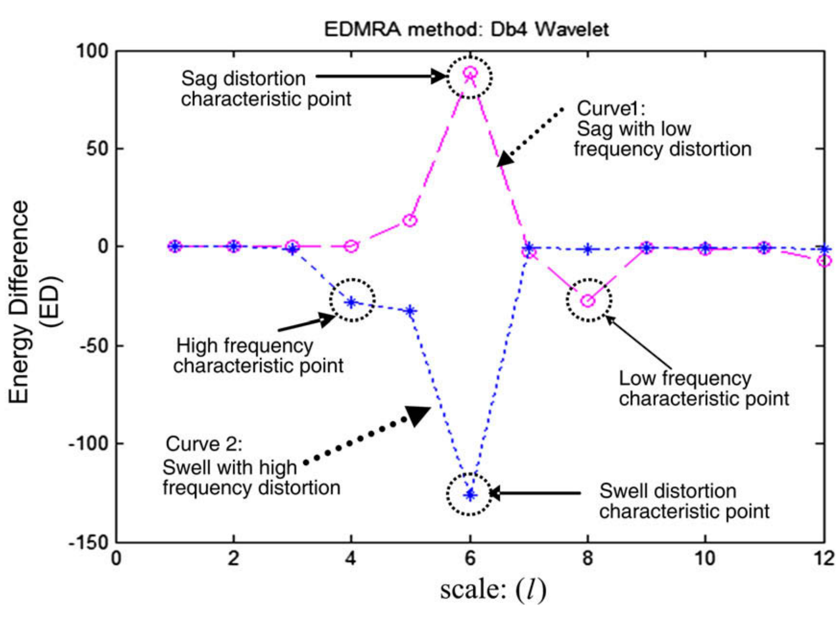

Fig. 8. EDMRA analysis result for the joint distortion of frequency and amplitude.

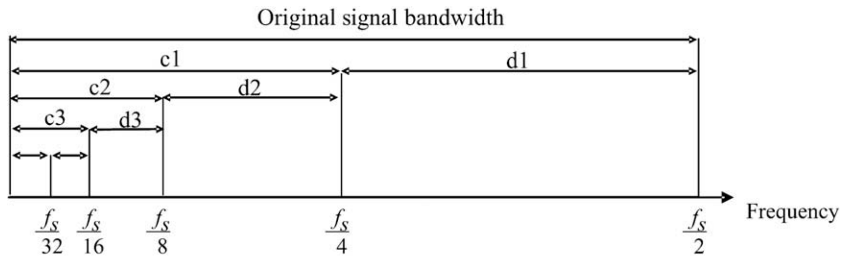

Fig. 9. The wavelet decomposition in the frequency domain.

Table 1
Frequency range of the MRA decomposition.

Decomposition level (l)	Frequency range	
	Approximation information (A)	Detail information (D)
1	$0 \sim f_s/2^2$	$f_s/2^2 \sim f_s/2^1$
2	$0 \sim f_s/2^3$	$f_s/2^3 \sim f_s/2^2$
...	...	...
n	$0 \sim f_s/2^{n+1}$	$f_s/2^{n+1} \sim f_s/2^n$

is l, Table 1 shows the frequency range at each decomposition level based on the frequency decomposition shown in Fig. 9.

In the proposed EDMRA method, only the detail information at each decomposition level is needed. Assuming that the normal reference frequency of the power signal is f_{ref} (50 Hz or 60 Hz) and we want to locate the energy of this reference signal at level N. According to Table 1, we have

$$f_s/2^{N+1} \leqslant f_{ref} \leqslant f_s/2^N \tag{8}$$

From Eq. (8), we get

$$\log_2(f_s/f_{ref}) - 1 \leqslant N \leqslant \log_2(f_s/f_{ref}) \tag{9}$$

Since we need to locate the energy of the reference frequency at the center of the final result (level 6 as shown in Fig. 5), the MDL for the EDMRA methods, denoted as $N_{\min}$, is found by

$$N_{\min} = 2 * N \tag{10}$$

For instance, in Fig. 4, sampling frequency $f_s = 5000$ Hz, $f_{ref} = 60$ Hz, according to Eq. (9), we get:

$$5.3808 < N < 6.3808 \tag{11}$$

we should choose $N = 6$. According to Eq. (10), we get $N_{\min} = 2 * N = 12$. This is the reason why we choose 12 levels of decomposition in Fig. 5 and why the evaluation reference scale is 6 in the criteria proposed in Section 3.1.

For any actual sampled signal, Eqs. (9) and (10) give the most efficient way of finding the decomposition levels for the EDMRA method. For example, if we sample the same waveform in Fig. 4 by sampling frequency $f_s = 2500$ Hz, we find only 10 levels of decomposition is necessary according to Eqs. (9) and (10). Fig. 10 gives the analysis result of 10 levels decomposition for the same signal as shown in Fig. 4. Comparing the analysis results in Figs. 10 and 5, we can see that, 10 levels decomposition is enough for classification varies type of PQ disturbances in this situation ($f_s = 2500$ Hz). In this way, we saved about 17% of the computational time compared to the 12 levels of decomposition.

Now, we can modify the evaluation criterions in Section 3.1 to a universal form:

Conjecture 2:

(1) If the peak-value of the ED is located at scale of $N_{\min}/2$, the disturbance is either sag or swell (negative ED means swell and positive ED means sag).
(2) If the peak-value is at a scale smaller than $N_{\min}/2$, the disturbance is high frequency distortion; otherwise, it is a low frequency distortion.

The regions of this classification are shown in Fig. 10.

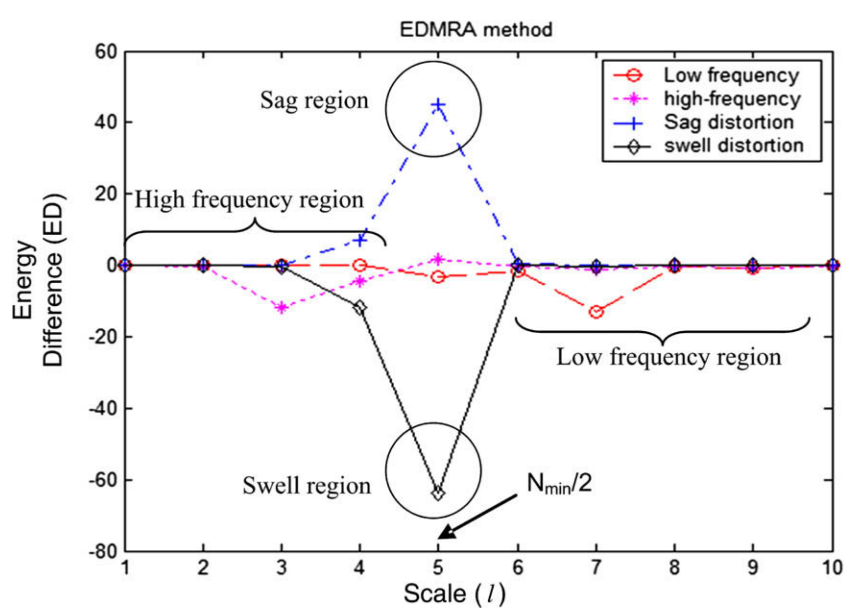

Fig. 10. Classification result of the EDMRA method.

Table 2
Wavelet characteristics.

Wavelet name	Orthogonal	Compact support	Support width	Filters length	Symmetry
Haar	Yes	Yes	1	2	Yes
Daubechies	Yes	Yes	2N-1	2N	Far from
Coiflets	Yes	Yes	6N-1	6N	Near from
Symlets	Yes	Yes	2N-1	2N	Near from

3.4. Choice of a suitable wavelet

It is well known that the choice of the appropriate wavelet is very important for all the wavelet based PQ analyses [4,16]. In this part, we investigate the influence of different kinds of wavelets to the proposed EDMRA method.

Four commonly used wavelets, namely, Daubechies wavelets, Symlets and Coiflets wavelet are taken into account. Notice that the Haar wavelets are Daubechies wavelets with $N = 1$. Table 2 shows their corresponding features and Fig. 11a–d is the EDMRA analysis result to the previous distorted signal in Fig. 4 (f_s = 5000 Hz, MDL = 12).

From Fig. 11a–d we can see, that although different wavelets have some influence of the final analysis result, all these wavelets keep good resolution to classify various type of PQ disturbances. By these means, we can claim that the EDMRA method has good robustness characteristics. However, it is very important to evaluate corresponding computational cost of different wavelets. This will provide useful information for actual application, considering the tradeoff between performance and time cost.

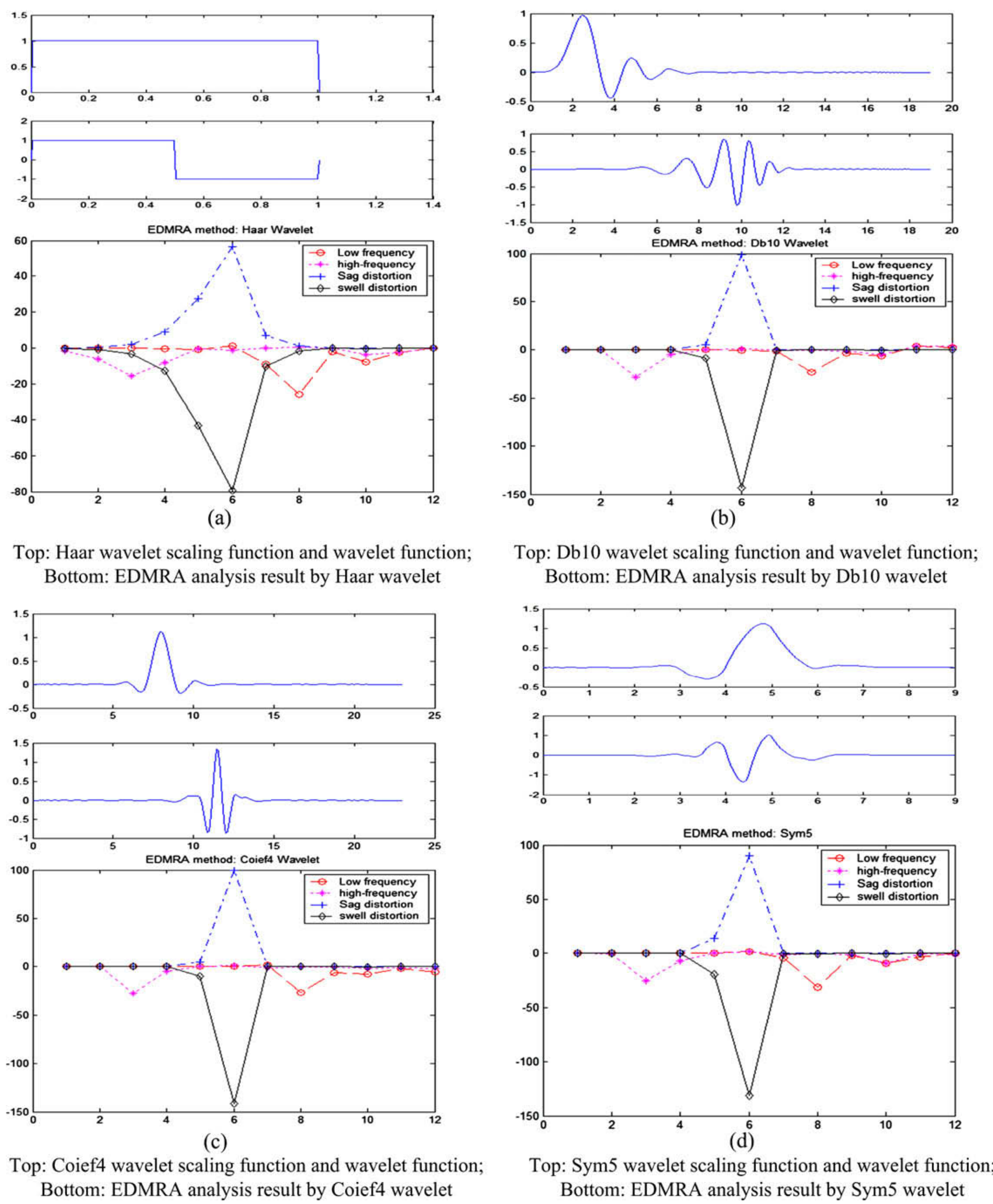

Fig. 11. EDMRA analysis results with different wavelets.

Table 3
Computational time for different wavelets.

Wavelets	Number of filter coefficients	Computational time (s)	$\Delta t\%$	Wavelets	Number of filter coefficients	Computational time (s)	$\Delta t\%$
Haar	2	0.5412	/	Sym 8	16	0.6100	12.71
Db2	4	0.5756	6.35	Coif 1	6	0.5733	5.93
Db5	10	0.5988	10.64	Coif 2	12	0.5875	8.55
Db8	16	0.6172	14.04	Coif 3	18	0.5984	10.56
Db10	20	0.6231	15.13	Coif 4	24	0.6119	13.06
Sym2	4	0.5681	4.97	Coif 5	30	0.6256	15.59
Sym5	10	0.5891	8.85				

Assume that the input discrete signal $x(t)$ is represented by a vector of length $N = 2^K$. The DWT using a wavelet with M filter coefficients, we need to compute

$$y_A[n] = \sum_{k=-\infty}^{\infty} x(k)c[2n-k] = \sum_{k=0}^{M-1} c[k]x[2n-k], \tag{12}$$

$$y_D[n] = \sum_{k=-\infty}^{\infty} x(k)h[2n-k] = \sum_{k=0}^{M-1} h[k]x[2n-k], \tag{13}$$

where y_A is the low pass component (approximation) and y_D is the high pass component (details) and $c[k]$ and $d[k]$ are the low pass (approximation) filter and high pass (detail) filter coefficients as defined in the dilation equations:

$$\phi(t) = \sum_{k=0}^{M-1} c[k]\phi(t-k) \quad \text{and} \quad \psi = \sum_{k=0}^{M-1} h[k]\phi(t-k), \tag{14}$$

where $h[k] = (-1)^k c[M-k]$, M is the filter length (total number of filter coefficients). Notice that when the DWT applied to discrete signal (a vector), the computation is simply the convolution of two vectors, the signal and the filter coefficients. After a type of wavelets is chosen, the length of wavelet filter will be kept the same at all levels. For this reason, the computation complexity is mainly dependent on the length of the wavelet filters. Since the mother wavelet produces all wavelet functions (via the dilation equations) used in the transformation through translation and scaling, it determines the characteristics (such as smoothness, symmetry) of the resulting Wavelet Transform. Therefore, the details of a particular application should be taken into account and the appropriate mother wavelet should be chosen in order to use wavelet transform effectively. For example, the Coiflets have important near symmetry property which is highly desired in image processing, since they correspond with nearly linear phased filters. Certainly, if the computational complexity is the only factor under consideration, the filter length should be chosen as short as possible.

From Section 2, we see that, the time complexity is proportional to the number of filter coefficients, thus wavelets with larger number of coefficient take longer time to compute. To gain empirical understanding of the computational complexity of different wavelet families, we conducted the experiments in Matlab 6.2 by Intel Pentium 4 1.8 GHz processor using a stopwatch timer. The computational time for Haar wavelet is chosen as the base for evaluation and we define the following variable $\Delta t\%$ for reference

$$\Delta t\% = \frac{t_{wavelets} - t_{Haar}}{t_{Haar}}, \tag{15}$$

where $t_{wavelets}$ means the EDMRA method computational time by the specific choosing wavelets, t_{haar} is the reference computation time of the EDMRA method by Haar wavelet. $\Delta t\%$ means how much more computational time should the specific choice of wavelet needed for EDMRA method compared to that of Haar wavelet. Based on the above definition, Table 3 gives the results according to Eq. (15).

Based on the data in Table 3, although Haar wavelet has the smallest computational cost, further investigation shows that Haar wavelet has difficulty to localize the time information for the beginning and ending time of the disturbance. Therefore, in the situation that the classification of different kinds of PQ disturbances is the only concerned issue, we can choose Haar wavelet for EDMRA method to avoid unnecessary computational cost. Otherwise, based on the data in Table 3, we recommend using wavelets with shorter filter length, such as Db2, Sym2 or Coif1 wavelets for practical application since they have relatively smaller computational cost as well as more reliable analysis performance. Of course, this kind of selection should also be based on their noise tolerance performance in actual applications, which will be discussed in detail in Section 4.

4. Noise tolerance analysis for EDMRA method

Since noise is omnipresent in electrical power distribution networks, we analyze whether the proposed EDMRA method is still effective in a noisy environment. Two types of noise, namely Gaussian white noise and band limited spectrum noise are considered.

4.1. Gaussian white noise

Gaussian white noise was considered in papers [18,23,24] for power quality disturbance analysis. In this section, we suppose that the noise riding on the sampled signal for EDMRA analysis is white Gaussian distribution. Here we focus on the detection and classification of different kinds of PQ disturbances under different signal to noise ratio (SNR). A detailed discussion about the localization of the beginning and ending time of the disturbances in noise environment can be referred in paper [18], in which an adaptive threshold of wavelet analysis is proposed to eliminate the noise influence.

Fig. 12 shows the EDMRA analysis result for the signal in Fig. 4 in the noisy environment with SNR = 20 dB. Comparing Fig. 12 with Fig. 5 we can see, the EDMRA method has good anti-noise performance and allow us to correctly classify different kinds of PQ disturbances in the noisy environment.

To test the EDMRA method performance in different noise environments, we use Monte-Carlo method to get the average correct classification rate when SNR varied from 20 dB to 50 dB. The value of SNR is defined as follows

$$SNR = 10\log(P_s/P_n)dB, \tag{16}$$

where P_s is the power (variance) of the signal and P_n is that of the noise. For each PQ disturbance, 100 cases with different parameters were simulated for each choice of wavelets. The average correct classification rate according to the evaluation criteria proposed in Section 3 is calculated for different wavelets under different SNR. The test results are shown in Fig. 13a–d.

4.2. Band limited spectrum noise

In real electrical distribution networks, noise caused by power electronic devices, control circuits, loads with solid-state rectifiers

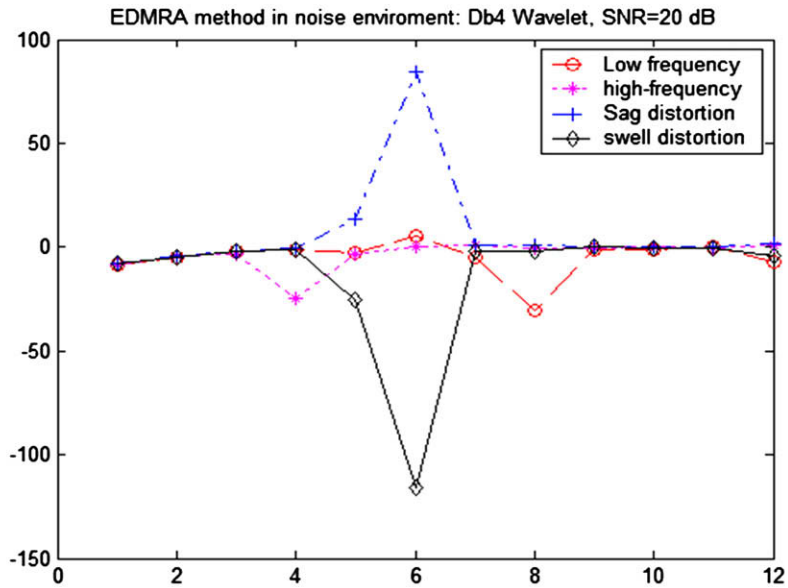

Fig. 12. EDMRA analysis result in Gaussian white noise environment (SNR = 20 dB).

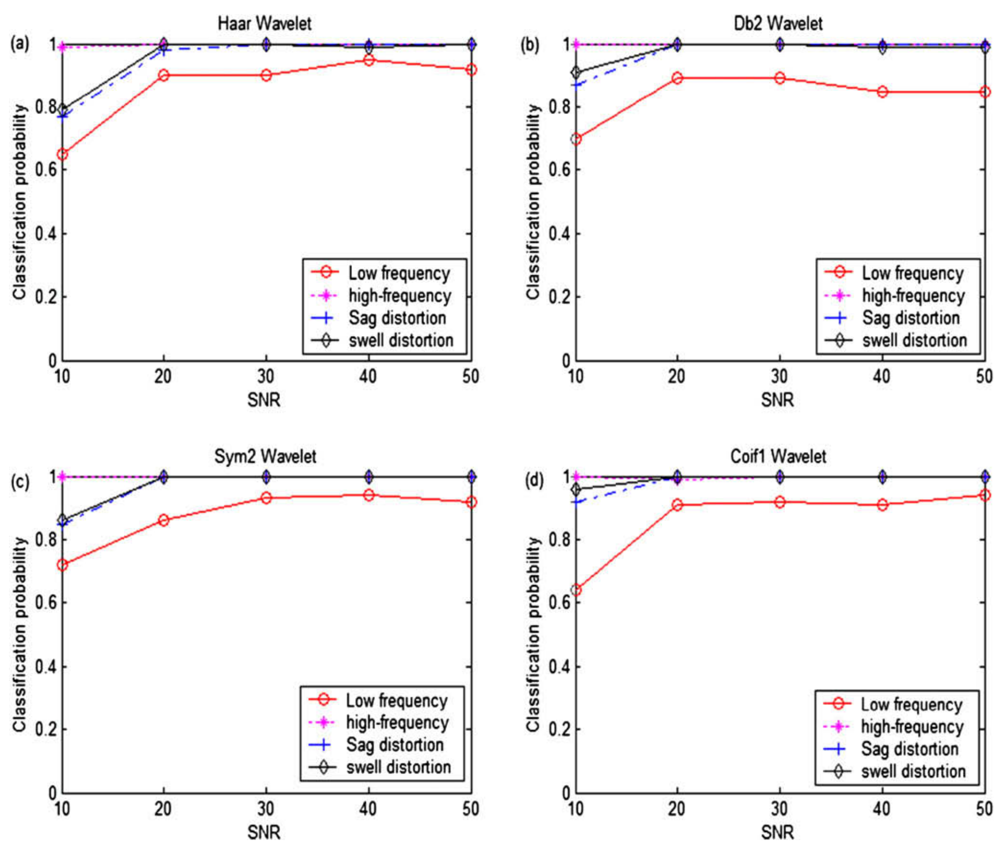

Fig. 13. Classification accuracy for different wavelet under different SNR.

and switching power supplies are not Gaussian white noise. It has been shown that the power quality noise is defined as electrical signals with broadband spectral content lower than 200 KHz superimposed upon the signal [25]. In this research, we consider a band limited noise spectrum close to the fundamental frequency (60 Hz).

Fig. 14 shows the EDMRA analysis (Db4 wavelet, SNR = 20 dB) result for the distorted signal combined with a band limited noise. As we can see here, the EDMRA method still shows good performance in this kind of noise environment.

To test the performance of different wavelets in different SNR within the band limited noise, Fig. 15 shows the Monte-Carlo

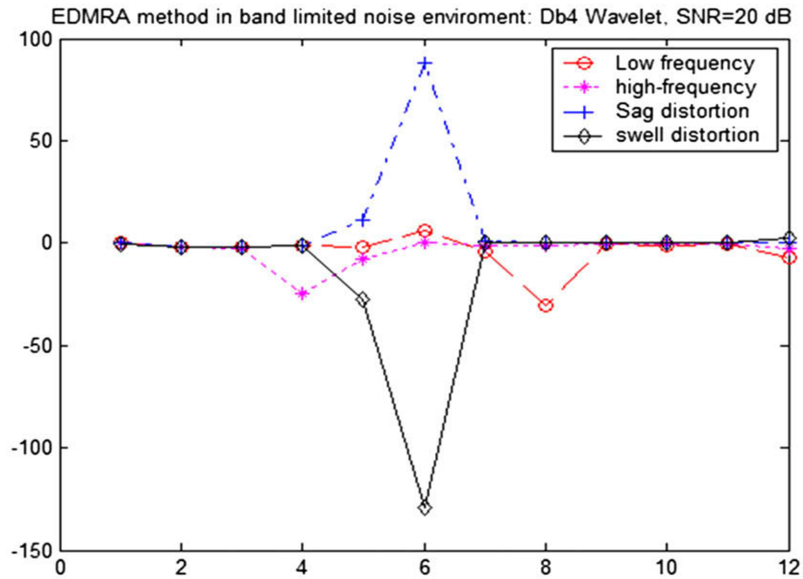

Fig. 14. EDMRA analysis result in band limited noise environment (SNR = 20 dB).

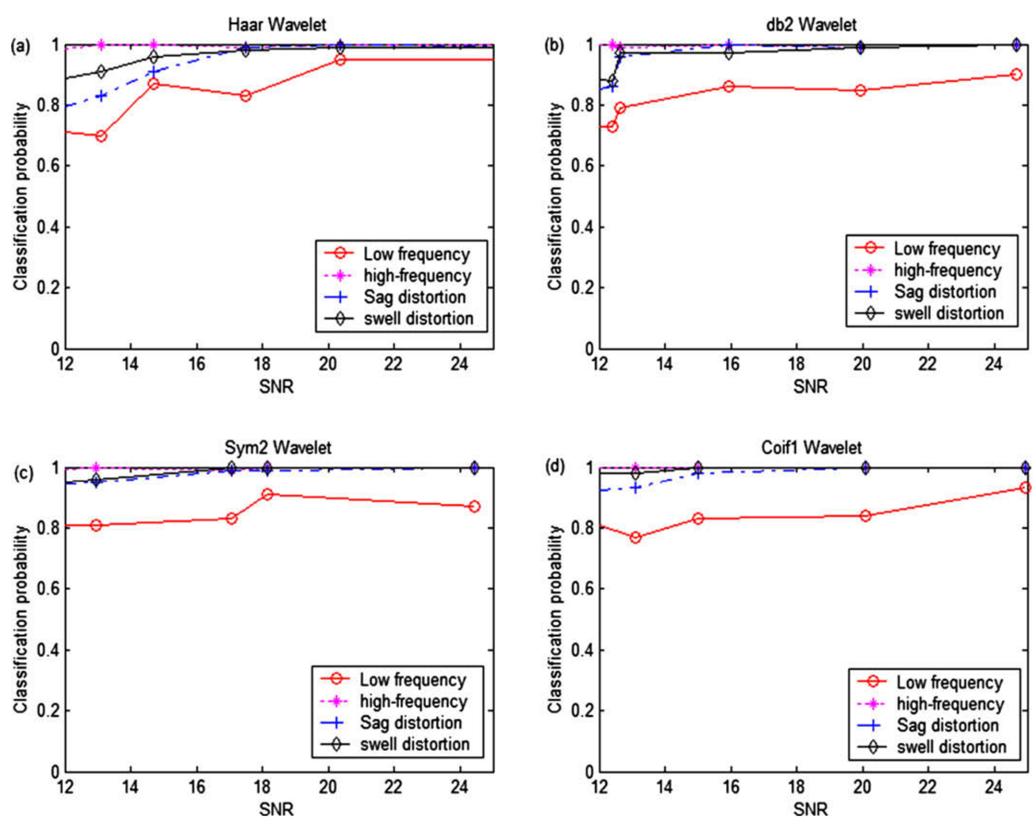

Fig. 15. Classification accuracy in band limited noise environment.

method for the average correct classification probability for different SNR.

Based on the analysis of the experimental results in Figs. 13 and 15, we conclude that the EDMRA method is not noise sensitive and performed well in the noisy environments. Although different types of noise and SNR have some influence on its performance, EDMRA method always can achieve high correct classification probability as presented in Figs. 13 and 15.

5. Conclusions

This paper presents an effective EDMRA method for detection, localization and classification of different kinds of PQ disturbances. The functional relationship between the MDL and sampling frequency is presented to avoid unnecessary computational cost. Different kinds of wavelets are taken into account in this paper and it is recommended that one can choose wavelets with short filter length, such as Db2, Sym2 or Coif 1 for practical applications based on their satisfactory performance as well as lower computational cost. Finally, two types of noise, named Gaussian white noise and band limited spectrum noise, are considered in the analysis. Monte-Carlo simulations are used to show the effectiveness of the proposed method in different noise environments empirically.

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