A NEW DSP TECHNIQUE FOR DISTURBANCE DETECTION, CLASSIFICATION AND MONITORING

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ABSTRACT

A new technique that can be implemented for power quality monitoring is proposed. A Windowed Wavelet transform and monitoring the maximum coefficient at each resolution are used to design a new monitoring tool with high accuracy. In this paper the proposed technique is verified by monitoring distorted signals, detect and localize these disturbances in time and generate stable features of the 50Hz component during signal's magnitude variation and phase shift changes in a noisy environment.

INTRODUCTION

The features extracted from power system disturbances could be detected for various time intervals and localized anywhere in a wide frequency band. These disturbances could be of high frequency nature such as transient events, periodic such as harmonic distortion or could be at the power system frequency (50 or 60 Hz) such as sag and swell phenomena. Disturbances could have steady-state or non stationary behavior [1]-[2].

A major concern arising from power quality monitoring is the size of data to be collected and the number of techniques to be implemented. Different data loggers are available that can collect large amount of data. Monitoring the wide band, where a distortion event may take place, requires a high sampling rate which results in capturing large data that may lead to rewriting over the oldest stored data or requiring additional high cost storing devices. The other major concern is the number of techniques, such as Fast Fourier transform (FFT), short time Fourier transform (STFT), Wavelet transform (WT), to be implemented in designing a tool that can monitor simultaneously low frequency or harmonic distortion, long and short duration variations, transient events and non-stationary disturbances that varies in frequency and/or magnitude.

Power system disturbances are classified in different categories according to magnitude, time duration and frequency content [1]. Basis such Fourier, Gabor, wavelet, and wavelet-packets are efficient representation for certain classes of signals, but there are many cases where a single basis system is not effective. For example, the Fourier basis is an efficient system for harmonic distorted periodic signals, but poor for transient and non-stationary signals.

Significant improvements in monitoring efficiency can be achieved by combining several basis systems [7]. That is can be achieved by designing a single expansion system ($\chi_{k,n}(t)$) to handle several different classes of signals, each of which are well-represented by a particular basis system. However, there are different criteria that have been identified as important and should be considered to approve the new basis system:

Sparsity: The expansion coefficients of any distortion event should have most of important information in the smallest number of coefficients so that the others are small enough to be neglected or set equal to zero. This is important for data management, compression and denoising.

Separation: Power system disturbances consist of a linear combination of signals with different characteristics, the expansion coefficients should clearly separate those signals. Features of interest that classify each disturbance should be separated and localized at different resolutions. This is important for detection and classification.

Super-resolution: A distortion event superimposed on a pure 50Hz component and its characteristic set of expansion coefficients should have much better resolution than that with a traditional basis system. This is likewise important for detection, classification and estimation.

Stability: The expansion coefficients that extracted from a reference signal (50Hz) should not be significantly changed by disturbances or noise. This is important in auto-monitoring application and data measurement.

Speed: The numerical calculation of the expansion coefficients in the new system should be of order $O(N)$ or $O(N\ log(N))$. This is important for real-time application.

The goal of this paper is to introduce Windowed-Wavelet transform as a new tool that can enhance wavelet based tools. The proposed tool generates stable features of the 50Hz component during signal variation and phase shift changes in a noisy environment. The proposed technique can be applied to monitor all expected power quality problems.

WAVELET MULTI-RESOLUTION ANALYSIS

Wavelet analysis techniques have been proposed extensively in the literature as a new tool for monitoring and analyzing different power system disturbances, data compression and de-noizing [3]-[5]. The wavelet transform is a mathematical tool that cuts up data, functions or operators into different frequency components, and then studies each component with a resolution matched to its scale [6]. The discrete wavelet transform (DWT) represents the signal $x(t)$ as a series of approximate $c_j(k)$ and detail $d_j(k)$ expansion coefficients.

$$x(t)=\sum_k c_o(k)\phi\,(t-k)+\sum_k\sum_{j=0}^{J-1} d_j(k)2^{j/2}\psi(2^j t-k) \quad (1)$$

The discrete wavelet coefficients measure the similarity between the signal and the selected wavelet $\psi(t)$; hence give a time-frequency localization of the signal. Using Mallats's algorithm, the detail coefficients at resolution *(j-1)* are:

$$d_{j-1}(k)=\sum_m h_1(m-2k)\ c_j(m) \quad (2)$$

where $h_1(k)$ represent the coefficients of the selected wavelet function. These expansion coefficients represent a components that are local and easier to interpret [8].

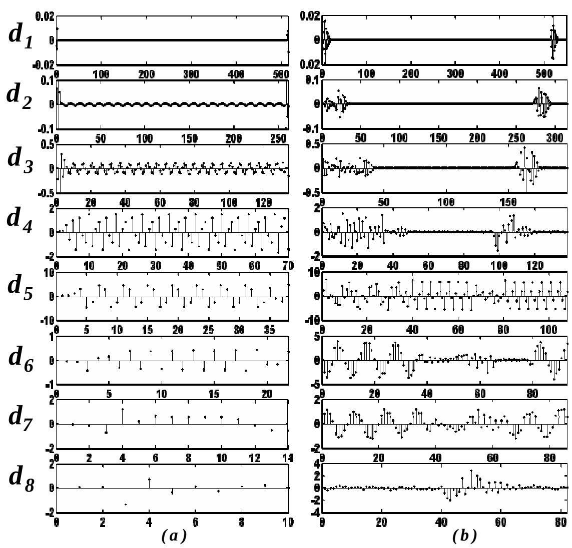

Fig. 1. Direct application of WMRA on a pure signal using a- *Db4* wavelet, b- *Db40* wavelet

Having 50Hz (or 60Hz) reference pure signal is an important advantage in power system applications as compared with other disciplines. This advantage should be efficiently utilized by defining the resolution levels that contains the 50Hz signal as a *reference resolution* to monitor normal and abnormal operation conditions. Fig. 1 shows 8 resolutions of the wavelet expansion coefficients of a 50Hz pure signal. *Daubechies 4* (Fig. 1a) and *Daubechies 40* (Fig. 1b) were used to decompose the signal. As exposed by the Figure, most of the pure signal energy is localized at the 5th resolution (*reference resolution*) as presented by the detail coefficients (d_5). However, other sets of coefficients are leaked and localized at other upper and lower resolutions. This leakage in the expansion coefficients comes partially from overlapping region due to the non-sharp cut–off frequency response of the selected mother wavelet. Further, in DWT the expansion coefficients c_j and d_j are resulted from convolution and decimation. Convolving the wavelet filter coefficients by the approximate coefficients may generate a set of coefficients at the start and end of the process that does not represent the signal at that resolution (for example, d_1, d_2 and d_3 in Fig. 21). These coefficients will generate other coefficients at other resolutions and hence scatters the pure signal's energy from the *reference resolution* to other resolutions. Furthermore, besides the computational complicity, while considering mother wavelets with high vanishing moments, all coefficients should be considered in the monitoring and classification process.

ENHANCING WAVELET MONITORING

One may design a single expansion system that handle several different classes of power distorted signals by developing a local trigonometric (local cosine and local sine) basis systems. In order to construct the trigonometric bases we have to choose a window function $w_k(t)$ and a trigonometric function $\upsilon(t)$ to generate orthogonal basis $\chi_{k,n}(t)$, that can be represented as [7]:

$$\chi_{k,n}(t)=w_k(t)\,\upsilon(t) \quad (3)$$

and

$$\upsilon(t)=cos(\alpha\pi\,(n+\beta)t+\gamma) \quad (4)$$

Trigonometric functions are selected because windowed trigonometric bases can be orthonormal, and the window can have a finite Heisenberg product [7].

Therefore using (3), any power signal $f(t)$ can be represented in terms of the expansion coefficients a_k in the form:

$$f(t)=\sum_{k,n} a_k(n)\chi_{k,n}(t) \quad (5)$$

By requiring orthogonality of the basis functions, the expansion coefficients are computed by an inner product as:

$$a_k(n)=\langle f(t),\chi_{k,n}(t)\rangle=\int f(t)w_k(t)\upsilon(t)\,dt \quad (6)$$

Any power quality phenomena as indicated in [1] and [2] can be simulated in terms of summation of different trigonometric signals. Therefore, we may strengthen the important criteria (sparsit, separation, super-resolution, and stability) by increasing the similarity between the signal under process and the basis system. This can be achieved generating a windowing version of the signal $w_k(t)\ f(t)$ that will increase the similarity between the signal under process and the selected wavelet function. Kaiser's window of length L is selected in the windowing process, which mathematically presented as:

$$w[n] = \frac{I_o\{\beta[1-(n-M)^2 / M^2]^{0.5}\}}{I_o(\beta(0,\alpha))} \quad \text{for } n = 0,1,....,L-1 \tag{7}$$

Using Mallat's algorithm, the set of expansion coefficients resulted form a windowing version of the signal at certain resolution can be defined as:

$$wd_j(k) = \sum_m h_1(m-2k)\ wc_{j+1}(m) \tag{8}$$

A threshold value (θ) is used to ignore the coefficients of small values. The threshold value is selected by monitoring the maximum coefficients extracted from a pure 50Hz component at each resolution level using WMRA and proposed technique. The selected threshold values (excluding the 5th resolution) in this application is 105% of the values indicated in Table I. The value of the maximum coefficient at the 5th resolution is normalize and used to monitor magnitude variation at that resolution. The absolute value of the detail coefficients ($|wd_j(k)|$) are used to localize either positive or negative expansion coefficients that carry most of the signal's energy.

Table I: Threshold values

Resolution Level	1	2	3	4	5	6	7
$\vert wd_j \vert_{Max}$	0.0100	0.0182	0.0579	0.4555	4.5100	0.6003	0.4931
$\vert d_j \vert_{Max}$	0.0189	0.0538	0.2071	1.6083	6.6424	4.8153	2.4778

Only the maximum coefficient can be considered in this application for monitoring the distorted signal.

$$[wd_j(N_j)]_{Max} = Max\ [wd_j(k)]_\theta \tag{9}$$

where, N_j are indices of the localized coefficients.

APPLICATION AND RESULTS

The proposed technique in this paper was evaluated by monitoring the changes in the 50Hz component of a simulated signal using Matlab. The results of the proposed technique are compared with that of applying directly the wavelet multi-resolution analysis. The simulated signal constructed from a pure signal that vary in magnitude and phase shift as follows:

$$f(t) = \begin{cases} 1.0\sin(\omega t) & t \le t_1 \\ 0.5\sin(\omega t - \pi) & t_1 < t < t_2 \\ 1.5\sin(\omega t - \pi) & t_2 < t < t_3 \\ -0.5\sin(\omega t - \pi) & t_2 < t < t_4 \\ 1.0\sin(\omega t) & t > t_4 \end{cases} \tag{10}$$

The distorted signal is simulated with a sampling rate of 2.2kHz. The size of Kaiser's processing window is selected with a length of 6-cycles and the coefficient α for Kaiser's window is selected equal to 10. The sliding rate of Kaiser's window is selected as 22 samples (1/2 cycle). The following features are considered in monitoring the resolution where 50Hz component reside:

1. The magnitude variation of the maximum coefficient at 5th resolution.
2. The stability of the index of the maximum coefficient at the 5th resolution (Coefficient location).
3. The sign of the maximum coefficient as data slides into Kaiser's window (Coefficient sign).

The comparison between a directly application of wavelet multi-resolution analysis (WMRA) and the proposed technique is shown in Fig. 2 and Fig. 3.

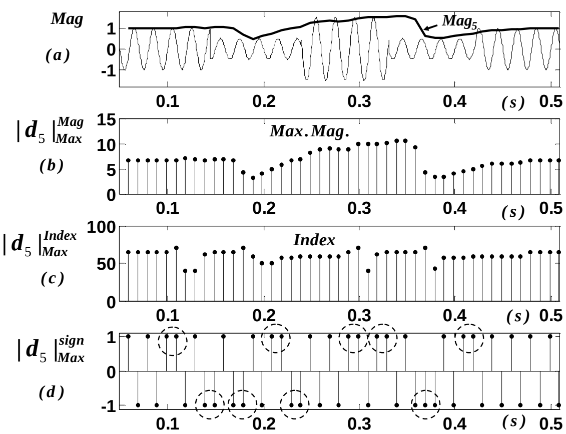

Fig. 2:Monitoring the maximum coefficient at 5th resolution using WMRA.

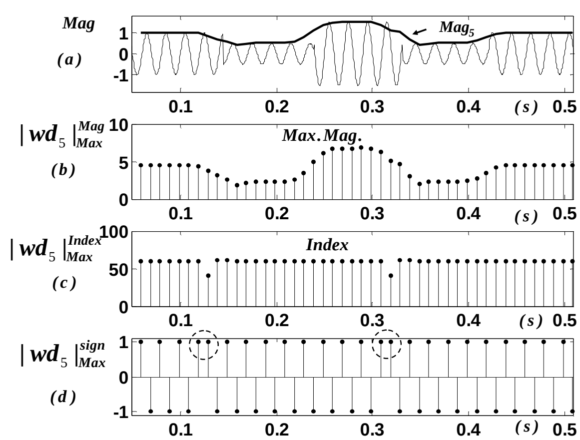

Fig. 3: Monitoring the maximum coefficient at 5th resolution using the proposed technique.

Fig. 2 shows the results of monitoring the maximum coefficient at the 5th resolution using WMRA. Fig. 2a shows the simulated signal and the solid line represents the magnitude variation of the signal. This variation is measured using the normalized value of the maximum coefficients shown in Fig. 2b. The magnitude measurement show accurate results during normal operation condition. As signal variation starts WMRA can detect magnitude variation but can not trace these variation as the as data processed. Fig. 2c shows the index of the maximum coefficient data processed. This index is not stable, as signals' magnitudes vary the location of the maximum coefficients at 5th resolution change. During normal operation condition the sign of the maximum coefficient varies regularly between positive (*logic +1*) and negative (*logic -1*) as shown in Fig. 2d. As the phase shift in the signal is changed, the sign of the coefficients changes but in non-regular way as shown by the dotted circles on Fig. 2d. These changes in the sign represent the changes in the original signal peak due to phase shift.

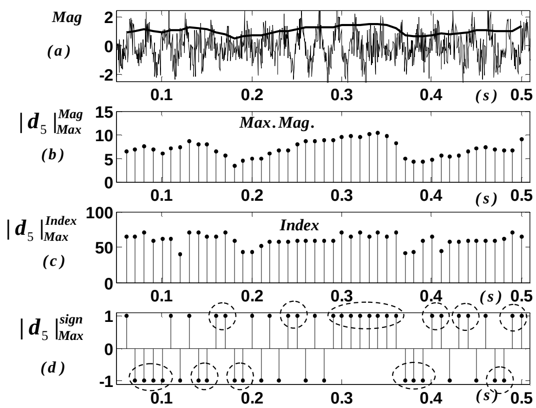

Fig. 4: Monitoring the maximum coefficient at 5th resolution of the signal distorted with high noisy level using WMRA.

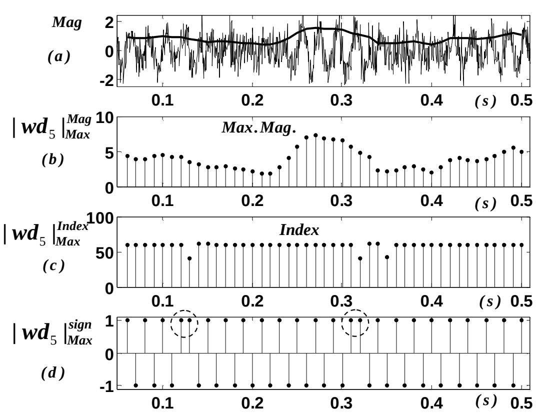

Fig. 5: Monitoring the maximum coefficient at 5th resolution the signal distorted with high noisy level using the proposed technique.

Fig. 3 shows the results of monitoring the maximum coefficient at the 5th resolution using the proposed technique. The variation in the magnitude is accurately traced as shown in Fig 3a. Fig. 3b and 3c show the magnitude of the maximum coefficients and their indices as data processed through Kaiser's window. The coefficient index is fixed and stable, as signals' magnitudes vary the location of the maximum coefficients at 5th resolution do not change. As the phase shift in the signal is changed, the sign of the coefficients changes in a regular way as shown by the dotted circles on Fig. 2d.

The simulated signal is further corrupted with a random noise of 75% in magnitude and the proposed technique is compared with a direct application of WMRA. The results of this comparison are shown in Fig. 4 and Fig. 5. The proposed technique show accurate and stable features with a noisy data. The magnitude, location and the sign of the coefficients are all stable similar to the case with zero noise level.

CONCLUSION

Disturbance can be detected, measured and classified by utilizing Windowed-Wavelet transform and monitoring the maximum coefficient at each resolution level. The proposed technique shows that we can generate a sharp reference and monitor different disturbances that may reside in different frequency bands by processing small numbers of expansion coefficients.

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REFERENCES

[1] IEEE recommended practices for monitoring electric power quality, IEEE std. 1159-1995, New York: IEEE, 1995.

[2] Roger C. Dugan, Mark F. McGranaghan, and H. Wayne Beaty, "*Electric Power System Quality*," McGraw-Hill 1996.

[3] David C, Robertson, Octavia I. Camps, Jeffrey S. Mayer, and William B. Gish, "Wavelets and Electromagnetic Power System Transients," *IEEE Transactions on Power Delivery Vol. 11, No.2, April 1996, pp1050-1058*.

[4] Santoso S., Grady W.M., Powers E.J., Lamoree J., Bhatt S.C., "Characterization of distribution power quality events with Fourier and wavelet transforms," *IEEE Trans. Power Delivery, vol. 15 , no. 1, pp.247–254, Jan. 2000*.

[5] A.M. Gaouda, E.F. El-Saadany, M.M.A. Salama, V.K. Sood, and A.Y. Chikhani, "Monitoring in HVDC Systems Using Wavelet-Multi-resolution Analysis," *IEEE Transaction on Power Systems, Vol. 16, No. 4, November 2001, pp.662-670*.

[6] John R. Williams and Kevin Amaratunga "Introduction to Wavelets in Engineering," *International Journal for Numerical Methods in Engineering, Vol.37, 2365-2388 (1994).*

[7] C. Sindney Burrus, Ramesh A. Gopinath, Haitao Guo, "Introduction to wavelets and Wavelet transform," Prentice Hall, New Jersey, 1997.

[8] Andrew Bruce, David Donoho, and Hong-Ye Gao "Wavelet Analysis," *IEEE Spectrum, pp 26-35, Oct. 1996.*

[9] Perrier, Philipovitch, and Basdevant, "Wavelet spectra compared to Fourier spectra," *Journal of Mathematical Physics, Vol. 36, No. 3, pp. 1506-1519, March 1995.*

[10] C. Sidney Burrus, James H. McClellan, A.V. Oppenheim, T.W. Parks, R.W. Schafer and H.W. Schuessler, "Computer-Based Exercises for Signal Processing using Matlab," Matlab Curriculum Series, Prentice hall, 1994.