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.

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-noising [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.

$$x(t) = \sum_k c_j(k) \phi(t-k) + \sum_{j=1}^{\infty} d_j(k) 2^{j/2} \psi(2^j t-k)$$

(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 Mallat’s algorithm, the detail coefficients at resolution $(j-1)$ are:

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

(2)

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

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 $v(t)$ to generate orthogonal basis $\zeta_{a,n}(t)$, that can be represented as [7]:

$$\zeta_{a,n}(t) = w_k(t) v(t)$$

(3)

and

$$v(t) = \cos(\alpha n + \beta t + \gamma)$$

(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:

$$f(t) = \sum_{k,n} a_k(n) \zeta_{a,n}(t)$$

(5)

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

$$a_k(n) = \langle f(t), \zeta_{a,n}(t) \rangle = \int f(t) w_k(t) v(t) dt$$

(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:
\[
w[n] = \sum_{i=1}^{L} \left( \frac{1 (n-i+1)}{M^i} \right) I_i \left( \beta \left( \frac{\alpha}{\alpha_i} \right) \right)
\]
for \( n = 0, 1, \ldots, L-1 \) \( (7) \)

Using Mallat’s algorithm, the set of expansion coefficients resulted from a windowing version of the signal at certain resolution can be defined as:
\[
wd_j(k) = \sum_m h_j(m-2k) \text{ } wc_j(m)
\]
\( (8) \)

A threshold value \( (\theta) \) 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 \( 5^{th} \) resolution) in this application is 105% of the values indicated in Table I. The value of the maximum coefficient at the \( 5^{th} \) resolution is normalized 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

<table>
<thead>
<tr>
<th>Resolution Level</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>(</td>
<td>wd_j</td>
<td>_{max} )</td>
<td>0.0100</td>
<td>0.0182</td>
<td>0.0579</td>
<td>0.4555</td>
<td>4.5100</td>
</tr>
<tr>
<td>(</td>
<td>d_j</td>
<td>_{max} )</td>
<td>0.0189</td>
<td>0.0538</td>
<td>0.2071</td>
<td>1.6083</td>
<td>6.6424</td>
</tr>
</tbody>
</table>

Only the maximum coefficient can be considered in this application for monitoring the distorted signal.
\[
[wd_j(N_j)]_{max} = \text{Max} [wd_j(k)] \theta
\]
\( (9) \)

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:
\[
f(t) = \begin{cases} 
1.0 \sin(\omega t) & t \leq t_1 \\
0.5 \sin(\omega t - \pi) & t_1 < t < t_2 \\
1.5 \sin(\omega t - \pi) & t_2 < t < t_3 \\
-0.5 \sin(\omega t - \pi) & t_3 < t < t_4 \\
1.0 \sin(\omega t) & t > t_4
\end{cases}
\]
\( (10) \)

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 \( \alpha \) 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 \( 5^{th} \) resolution.
2. The stability of the index of the maximum coefficient at the \( 5^{th} \) 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.
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.

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