Feature extraction of Power Quality disturbances using Adaptive Harmonic Wavelet Transform

Pramod Chand, MS Control Systems, WVU Tech

Asad Davari, PhD., ECE Department, WVU Tech

Bao Liu, PhD., Math Department, WVU

Kourosh Sedghisigarchi, PhD., ECE Department, WVU Tech

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Abstract--**Feature extraction of a disturbed power signal provides information that helps to detect the responsible fault for power quality disturbance. A precise and faster feature extraction tool helps power engineers to monitor and maintain power disturbances more efficiently. This paper uses adaptive harmonic wavelet transform as a power quality feature extraction tool which can perform better to analyze a disturbed voltage or current signal compared to present methods. Adaptive harmonic wavelet transform adopts harmonic wavelet as a basis function which provides better representation of power quality signals than the other wavelet functions that are being employed in present analysis tools. Adaptive harmonic wavelet transform is derived from generalized harmonic wavelet transform by developing its adaptiveness to analyze all kinds of disturbed signals with minimum human interaction.**

I. INTRODUCTION

Modern industrial, commercial as well as household equipment use microprocessor-based systems that are sensitive to the power quality provided by their utility company. Poor power quality can cause serious problems to those devices causing malfunction, instability, short lifetime, memory loss, data errors and so on. To obtain steady and high-quality electricity, customers prefer a power company that has regular control over their supply. To supply high-quality power the supplied voltage and current waveforms must be maintained nearly sinusoidal shape with constant frequency and amplitude all the times. Even though high quality of electricity is generated in the power plants, during the transmission period the quality can diminish by for instance faults, equipment interactions, switching operations and improper wirings and groundings. In order to maintain the quality electricity, power companies need to monitor and maintain their supply all the time. At each event when the supplied voltage falls out of tolerable range of the standard set by the American National Standard Institute (ANSI), the condition should be assigned a very high priority and effort should begin immediately to correct the voltage to an improved range.

It is a challenge for a power company to regularly monitor the electricity they supply. In practice, power quality monitoring is done at every sub-stations of a system which each year produces high volume of data to be controlled. From such a high volume of data it is a laborious and time consuming process to identify disturbances, on-line or even off-line, using the conventional visual inspection method. In order to improve the quality of service, electric utility must provide real-time monitoring systems that are capable of identifying the signatures of different events and making prompt decision for maintenance. Feature extraction tool helps to achieve that promptness by retrieving the critical data representing any signal and reducing the dimensionality of the overall data. This paper focuses on the feature extraction stage which is the fundament of designing power quality monitoring tool.

We are proposing the use of adaptive harmonic wavelet transform [1] for the feature extraction of power signal. A power system is designed and the possible power quality disturbances events are simulated to generate disturbed power signal waveforms. Those waveforms are analyzed with adaptive harmonic wavelet transform as well as the other wavelet transforms that are currently being used for the feature extraction purpose. Then finally, the preciseness and speed of the data extracted by those methods are compared with that of adaptive harmonic wavelet transform to assure its superiority.

II. ANALYSIS METHODS

The main objective of signal analysis is to extract the discriminating frequency components and their respective time information. Since, Fourier transform (FT) assumes periodicity of a given signal and loses the time axis account, it is not capable of providing time information of signal disturbances. Short time Fourier transform (STFT) provides both time and frequency information, but it suffers severely from the Heisenberg Uncertainty principle [2] causing it to undergo a "trade-off" between time resolution and frequency resolution. Wavelet transform [3], which is a popular signal analysis method, offers continuous and discrete wavelet transforms (CWT and DWT) [4] and wavelet packet transform (WPT) [5] for the feature extraction of signals. This paper suggests that in the case of power signal analysis harmonic wavelet transform [6] can perform better than the other popular wavelet transforms. The power signals are basically non-stationary and periodic in nature, thus the application of available irregular shaped mother wavelets used by other wavelet transforms are not suitable for their analysis. For that purpose a mother wavelet is required which can correlate more with PQ signals for accurate result. Harmonic wavelet transform uses such mother wavelet that makes obvious difference in the preciseness of the result obtained. Harmonic wavelet transform provides more precise results faster than discrete wavelet transform.

Harmonic wavelets [6], that are generated by applying inverse Fourier transform to a band of frequency components, are the functions of frequency bands that correlate more accurately to power signals. The characteristic of harmonic wavelet makes it possible to generate non-overlapping orthogonal bases, whose spectrum is confined exactly to a desired frequency band. That property enables harmonic wavelet to analyze any frequency components of a signal by selecting corresponding band from the frequency domain of the signal and plotting in time-frequency plane. It allows harmonic wavelet transform to avoid the tiresome and prerequisite process of the use of correlated quadratic mirror filters like in DWT; therefore harmonic wavelet transform is highly desirable for the analysis of the signals composed of harmonics and transients such as power signals.

A. Harmonic Wavelet Transform

The discrete harmonic wavelet transform is defined as

$$W_{m,n,k}(\omega)=\begin{cases}\dfrac{1}{(n-m)2\pi}e^{(-j\omega\frac{k}{(n-m)})} & ,m2\pi\le\omega<n2\pi\\ 0 & ,otherwise\end{cases} \tag{1}$$

where m and n are the level parameter and $\frac{1}{(n-m)}$ is the scaling factor. $W_{m,n,k}(\omega)$ exists only within the frequency band of $m2\pi$ to $n2\pi$ otherwise it is zero.

Newland selected the parameter $m = 2^{j}$ and $n = 2^{j+1}$ to develop classical harmonic wavelet transform (CHWT) [6] which could generate orthogonal bases that are confined exactly to octave bands. As classical harmonic wavelet transform was unable to keep an account of each individual frequency component of an analyzed signal, in 1994 Newland came up with generalized harmonic wavelet transform (GHWT) [7] to obtain more elaborate time frequency analysis.

B. Generalized Harmonic Wavelet Transform

Newland proposed that if the pairs *m* and *n* begin with a pair for which $m = 0$ and continue with touching but not overlapping other pairs to the right, then the generalized harmonic wavelets generated by $W_{m,n,k}(\omega)$ and their complex conjugates provide a complete set of orthogonal basis function for expanding any arbitrary function of finite energy.

Generalized harmonic wavelet transform can provide richer signal analysis with great deal of freedom, but it faces the problem of selecting the m and n parameters. The selection is currently done empirically. It requires lots of trial and error methods or a priori knowledge to analyze a signal using GHWT. Such time consuming method can be avoided by using adaptive harmonic wavelet transform (AHWT) [1] which can adaptively select the discriminating frequency bands that are critical in shaping a given signal and provides precise and finer time-frequency resolution.

C. Adaptive Harmonic Wavelet Transform

Application of AHWT does not require knowing parameter m and n of the critical frequency bands a priori because the application of cost function and best basis selection method can automatically detect those important frequency bands [5].

The AHWT method basically consists of two parts. The first part is designing a partition tree and the second part is selecting the best partitions. Partition tree is a collection of disjoint partitions of the real frequency component where each parent node is further decomposed into children nodes respectively. As shown in Fig. 1, a partition tree consists of partition bands $\{P_l\}_{l=0}^{L-1}$, where: $L \le$ *Nyquist frequency* + 1. If the tree reaches its final level of partition then L = *Nyquist frequency* + 1. The total decomposition level of any tree can be calculated by $\frac{N_f}{2} \ge (dividend)^{\max.\,level}$, where dividend value represents the partition tree type and max level represents the maximum possible level of decomposition for that partition tree. Each partition band contains the frequency component of $P_l = \{K\,2\pi\}_{k=m_l}^{m_{l+1}-1}$, with $m_0 = 0$ and $m_L = N_f + 1$. Each of these partitioned frequency components correspond to an orthogonal harmonic wavelet basis that can represent the original signal. In order to address the partition bands the levels are denoted by *j* and the nodes by *n*.

Partition tree produces a large number of orthogonal bases among which only few such bases have the critical time-frequency data that are required as the feature of the signal. To select those best bases from a partition tree Shannon entropy of each node's wavelet spectrum is calculated.

$$\text{Wavelet Spectrum } (P_i)=\frac{1}{N}\left|\omega_{j,n}\right|^2 \tag{2}$$

where $\omega_{j,n}$ is the wavelet coefficients of a node *n* at level *j*. Wavelet Coefficients are obtained by applying inverse Fourier transform to the frequency nodes of the partition tree.

$$\text{Shannon entropy} = -\sum_{i=0}^{N-1} P_i \log_2 P_i \tag{3}$$

where P_i is the wavelet spectrum.

The calculated entropy values are used as cost functions of respective nodes and scanned through the best basis selection algorithm. After the best nodes are selected the frequency components in those nodes are plotted in time-frequency plane according to the weight of their $P_{j,n}$ values.

III. SIMULATION AND RESULTS

For simulation purpose one-line power system is designed using Simpower Systems Simulink [8]. The Fig. 2 power model contains AC voltage source with 60 Hz, 424.35 kV three-phase power systems where only one phase is shown. The source feeds a load and a capacitor through 200 miles long transmission line modeled by two PI sections and an equivalent circuit. The transmitted voltage is stepped down with transformers that eventually cut down the voltage level to

240 V. The load is connected with an inductor and a capacitor bank because the real-life loads are inductive in nature and reactive power has to be supplied to them from power factor correction capacitors. Circuit breakers are used to switch the load and the capacitor at the receiving end of the transmission line. Although the capacitor and inductor switchings is required to maintain power factor, it also generate transients to the power signal degrading the power quality. The one-line model shown in Fig. 2 is used to simulate capacitor switching transient in order to generate a disturbed power quality signal, as shown in Fig. 3. Some other simulated voltage signals with different kinds of disturbances are shown in Fig. 8. The voltage signal in Fig. 8 a, b, c and d suffers from impulsive transient, sag, gap and swell respectively. Since capacitor and inductor are reactive elements and their impedance change with the change in a phase angle of supplied voltage, each fault applied at different phase angle of the supplied voltage produces different kind of disturbances. When a capacitor switching is simulated at the phase angles of 0°, 90°, 120°, 270° and 360° of a supplied voltage signal it generates impulsive transients of different amplitude at different locations, as shown in Fig.9. The disturbed signals are simulated with a sampling time of .0001 second for .5 second. Each simulated signals contains 5000 samples. The generated signal data are further processed with Matlab codes, Matlab function libraries and Matlab Wavelet Toolboxes to obtain and compare results.

When the signal with oscillatory transients, shown in Fig. 3, is analyzed with both wavelet packet transform and AHWT and their results are compared, it can be concluded that AHWT provides better time-frequency analysis than the wavelet packet transform. Comparing Fig. 4 and 5 it can be concluded that AHWT provides much clearer and precise time-frequency resolution to that of wavelet packet transform that has lots of noises.

The calculation of AHWT suffers from rigidity of analyzing signals that have both harmonics and impulsive transients. The cost functions of harmonics always overweigh the cost functions of the imperceptible impulsive transients; therefore, it is required to get rid of the harmonics in order to analyze the signal's transients. For illustration, let's consider a 60 Hz voltage signal with transients as shown in Fig. 6. First the FFT of the signal is obtained to find out the dominant frequency components, which is only the 60 Hz of the voltage signal itself. If the signal had harmonics, their frequency values could also be obtained from the FFT. Those dominating frequency values are then replaced with insignificant values so that they no more overweigh the cost functions of the transients. From the Fig. 7 it can be seen that the transient of the voltage signal of Fig. 6, which was not visible in the presence of the dominating frequency of 60 Hz, appears in the time-frequency plot only after the overweighing values of the frequency band of 50-70 Hz is replaced with small values.

IV. CONCLUSION

Although wavelet packet transform is considered as an efficient signal analysis tool, its preciseness varies according to the nature of the signal being analyzed. For power quality signals like voltage and current signals adaptive harmonic wavelet transform can provide more precise analysis than the wavelet packet transform. AHWT can more efficiently separate the critical frequency components of a power quality signal and appears to perform better as a feature extraction tool than other signal analysis tools.

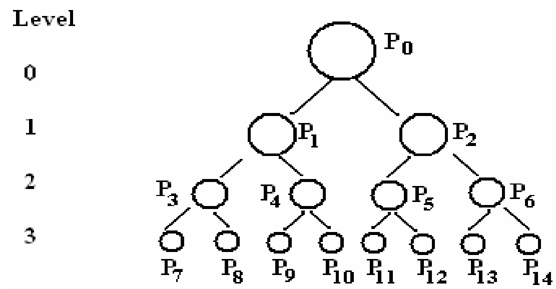

Fig. 1. A three-level binary partition tree with fifteen partition bands.

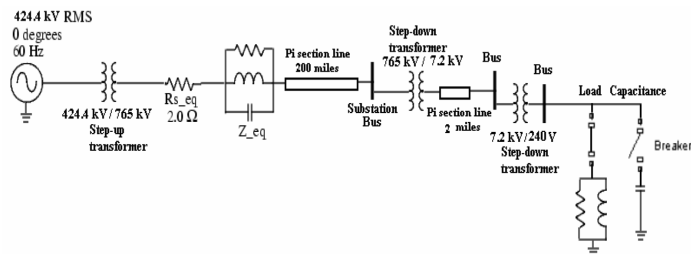

Fig. 2. One-line power model with load, capacitor and switches.

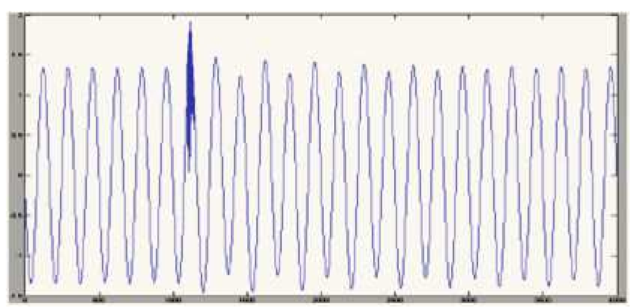
Fig. 3. A simulated voltage signal with oscillatory transients due to capacitor switching.


Fig. 4. Wavelet Packet's best tree analysis result for the above signal.

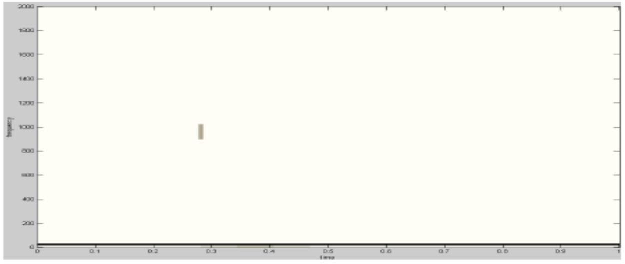

Fig. 5. Time-frequency resolution of the disturbed signal analyzed by AHWT.

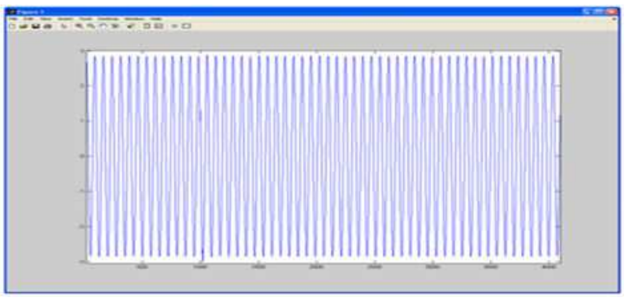

Fig. 6. A simulated voltage signal with impulsive transients.

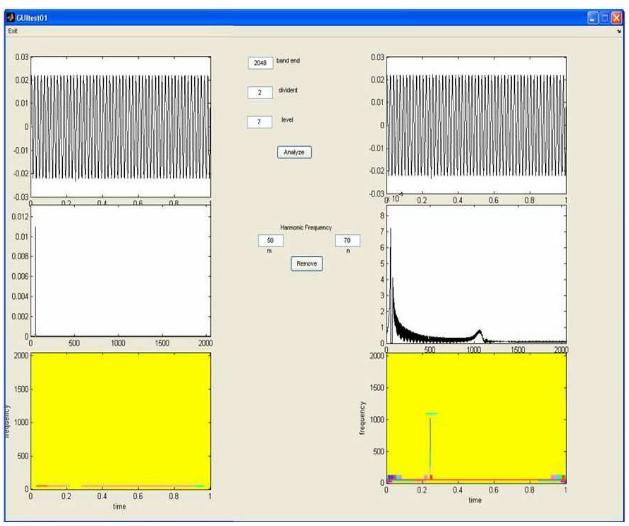

Fig. 7. GUI to illustrate that the impulsive transients are observable in AHWT analysis only after treating the dominant frequency components.

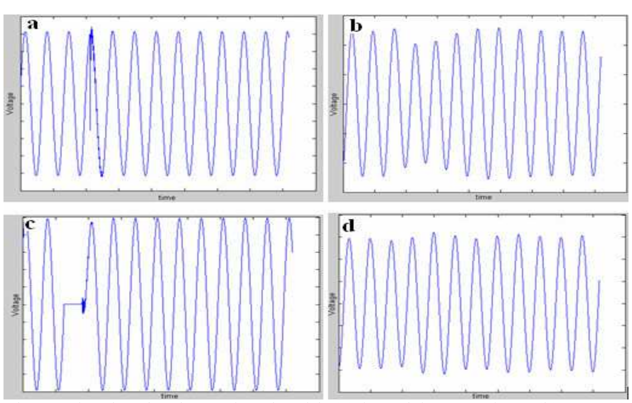

Fig. 8. Simulated voltage signals with (a) impulsive transient, (b) sag, (c) gap and (d) swell.

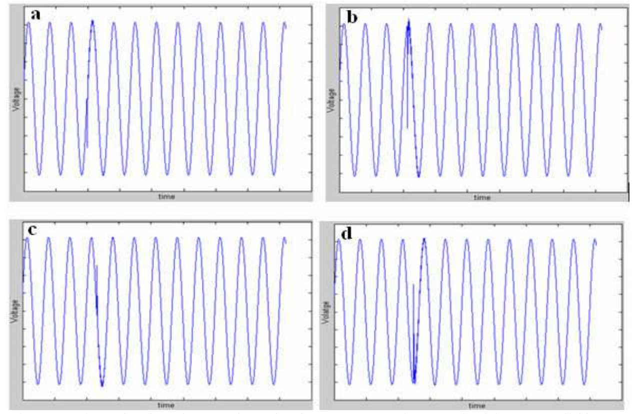

Fig. 9. Disturbed voltage signals due to capacitor switchings at different phase angles. (a) 0°, (b) 90°, (c) 270° and (d) 360°.

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