WAVELETS AND ELECTROMAGNETIC POWER SYSTEM TRANSIENTS

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Abstract The wavelet transform is introduced as a method for analyzing electromagnetic transients associated with power system faults and switching. This method, like the Fourier transform, provides information related to the frequency composition of a waveform, but it is more appropriate than the familiar Fourier methods for the non-periodic, wide-band signals associated with electromagnetic transients. It appears that the frequency domain data produced by the wavelet transform may be useful for analyzing the sources of transients through manual or automated feature detection schemes. The basic principles of wavelet analysis are set forth, and examples showing the application of the wavelet transform to actual power system transients are presented.

INTRODUCTION

The analysis of electromagnetic transients associated with an abnormal condition in a power system has always been fundamental to explaining and then correcting the cause of the condition. It is for this reason that well instrumented substations have transient event recorders. The recent conversion to digital transient recording (even by computer-based relays) has made much more data rapidly available to the engineer.

In digital form, the transient information is amenable to automated analysis. Present efforts for characterizing transients such as lightning and switching surges use parameters such as crest value, front time or time to crest, and time to half value. Standards have been established for obtaining these parameters graphically from recorded waveforms [1], and recently several methods have been proposed for extracting these data from digital recordings using curve fitting techniques [2, 3].

The volume of data necessary to capture valuable high-frequency information while retaining the dynamic response of the power system, if only for a fraction of a second, requires massive data storage and handling systems. Presently, taking full advantage of information about power system viability from transient responses is not practical. Even if rule-based analysis had been fully developed, the vast amount of data that has to be transferred to a central site for correlation with transient data collected at other points in the system would overwhelm communication channels. Until on-site, automated analysis becomes available, human evaluation of the data further requires that only the extreme transient cases receive any attention.

Ready access to transient data should permit the early detection of problems before disruptive or catastrophic events occur. Quite frequently these early warning events are at detection levels at or below normal transient events with larger crest values, front times, etc. To get past the data mountain barrier to see the truly useful transient information requires a new approach to raw digital data gathering.

The purpose of this paper is to introduce to the power engineering community a powerful new method for transient data capture and analysis. This paper is intended to be a timely and useful commentary on understanding and using the wavelet transform. The wavelet transform, which has received considerable interest in fields such as acoustics, voice communications, and seismics, is proposed as a fast and effective means of analyzing voltage and current waveforms recorded during power system disturbances. Like the familiar Fourier transform, the wavelet transform decomposes a signal into its frequency components. Unlike the Fourier transform, the wavelet transform provides a non-uniform division of the frequency domain. This ability to tailor the frequency resolution can greatly facilitate the detection of signal features which may be useful in characterizing the source of the transient or the state of the post-disturbance system.

The wavelet transform is well suited to wide-band signals that may not be periodic and may contain both sinusoidal and impulse components as is typical of fast power system transients. In particular, the ability of wavelets to focus on short time intervals for high-frequency components and long intervals for low-frequency components improves the analysis of signals with localized impulses and oscillations, particularly in the presence of a fundamental and low-order harmonics.

The remainder of this paper is organized as follows. The defining mathematics and a graphical interpretation of the wavelet transform is introduced through comparison with the Fourier and the Short-time Fourier transforms. The potential usefulness of the wavelet transform in providing easily detectable signal features is then demonstrated using recorded power system data.

WAVELETS AND FOURIER METHODS

A starting point for discussion of the wavelet transform and its properties is a comparison to Fourier analysis methods [4]. In particular, comparison of the wavelet transform to the Fourier transform illustrates the advantages of using the former over the latter in the analysis of transient signals.

The waveforms associated with fast electromagnetic transients are typically non-periodic signals which contain both high-frequency oscillations and localized impulses superimposed on the power frequency and its harmonics. These characteristics present a problem for traditional Fourier analysis because its use assumes a periodic signal and because a wide-band signal requires more

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dense sampling and longer time periods to maintain good resolution in the low frequencies. Still, it is desirable to apply a frequency-based analysis method in an attempt to isolate the transient components of the signal which may help in identifying the particular phenomena producing the transient.

The Fourier Transform

The *Fourier Transform* $X(f)$ of a continuous-time signal $x(t)$ is given by

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \ . \qquad (1)$$

The continuous function $X(f)$ is the frequency-domain representation of $x(t)$ obtained by summation of an infinite number of complex exponentials. To find $X(f)$ on a digital computer with discrete (sampled) and finite-length (time-limited) signals, the *Discrete Fourier Transform* (DFT) is used. The DFT is defined as

$$X[k] = \sum_{n=0}^{N-1} x[n]\, e^{-j\frac{2\pi kn}{N}} \qquad (2)$$

where $x[n]$ is a sequence obtained by sampling the continuous time signal $x(t)$ every T_s seconds for N samples:

$$x[n] = x(nT_s) \quad n = 0, 1, 2, ..., N-1 \ . \qquad (3)$$

The DFT produces a sequence of complex values $X[k]$ whose magnitudes are those of discrete frequencies in $x[n]$. Because the derivation of the DFT strictly requires $x[n]$ periodic, the representation of a signal by the DFT is best reserved for periodic signals. This and the Nyquist criteria–sampling at least twice as fast as the highest frequency in the signal–are two important caveats to using the DFT.

The limitations of the DFT for non-periodic signals can be illustrated using a signal containing a transient impulse with a ring of 900 Hz superimposed on a 60 Hz fundamental. Such a signal is typical of a capacitor switching transient. The transient signal and the resulting DFT output are shown in Figure 1, (a) and (b), respectively. The presense of significant energy in the sidebands of 900 Hz is a direct result of the non-periocity of the input. This can prevent precise detection of the resonant frequency of the capacitor-compensated system, a potential feature for determining the cause of the transient.

More sophisticated Fourier-based transforms have been developed to reduce the effect of non-periodic signals on the DFT. One such method, the Short-Time Fourier transform (STFT), assumes local periodicity within a continuously translated time window. The following sections discuss the STFT which will be useful in comparing the Wavelet and Fourier methods.

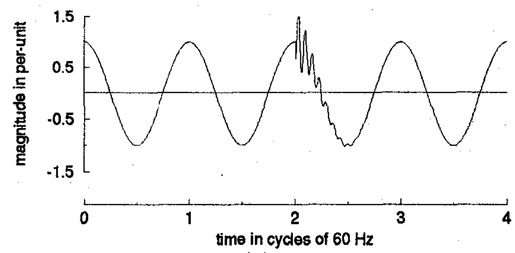
The Short-Time Fourier Transform

The STFT is similar to the Fourier transform except that the input signal $x(t)$ is multiplied by a window function $w(t)$ whose position is translated in time by τ:

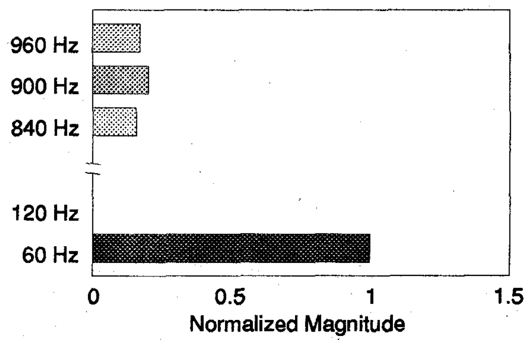
$$STFT(f,\tau) = \int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-j2\pi ft}dt \ . \qquad (4)$$

For digital implementation of the STFT, the Windowed Discrete Fourier Transform (WDFT) is used. The WDFT is defined as

$$WDFT[k,m] = \sum_{n} x[n]\, w[n-m]\, e^{-j\frac{2\pi kn}{N}} \qquad (5)$$



(a)



(b)

Figure 1: Transient signal with a localized oscillation within the sampling window and its discrete fourier transform

where the sequence $w[n-m]$, in its simplest form, is the rectangular window function

$$w[n] = \begin{cases} 1 & if\ 0 \le n-m \le N-1 \\ 0 & otherwise \end{cases} \ . \qquad (6)$$

For each window $w_{m_o} = w[n-m_o]$, the WDFT produces a sequence of complex values $WDFT[k, m_o]$, $k = 0, 1, ...N-1$, whose magnitudes are those of the discrete frequencies of the input $x[n]$.

The WDFT of a signal can be represented in a two-dimensional grid where the divisions in the horizontal direction represent the time extent of each window $w[n-m]$; the divisions in the vertical direction represent the frequencies k; and the shade of each rectangle is proportional to the corresponding magnitude. The DWFT in Figure 2(b) for the capacitor switching transient, contains the same frequency information as the previous DFT example with an additional dimension of time.

The time period of each window in Figure 2(b) T=16.67 ms fixes the frequency resolution Δf at 60 Hz ($\Delta f = 1/T$). This however locates the start time of the transient only to within one 60-Hz cycle. Shortening the window period by four as in Figure 2(c) locates the start of the transient but makes Δf four times larger. As a result of the lower frequency resolution of 240 Hz, the energy of the 60 Hz fundamental appears in the dc and 240 Hz components.

This example illustrates the need for multiple resolution in time and frequency for power signals containing a fundamental frequency superimposed with transients. More precisely, fine time resolution for short duration and high frequency signals, and fine frequency resolution for long duration and lower frequency signals are needed. This provides accurate location of the transient component while simultaneously retaining information about the fundamental frequency and its low-order harmonics.

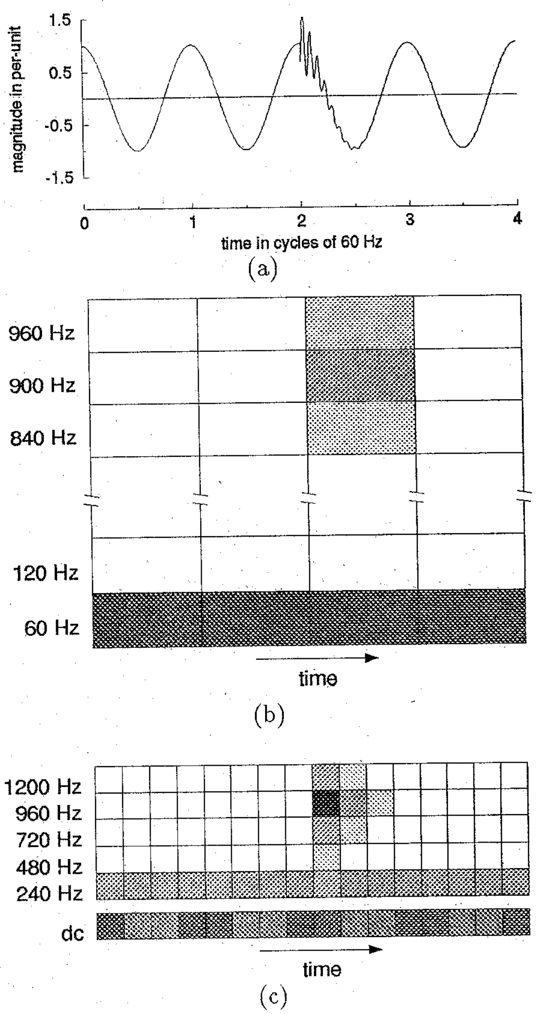


Figure 2: Windowed Discrete Fourier transform output for different window sizes: (a) example input signal, (b) *WDFT* with one-cycle window size, $\Delta f = 60$ Hz, (c) *WDFT* with quarter-cycle window size, $\Delta f = 240$ Hz.

The Wavelet Transform

The Wavelet Transform (WT) of a continuous signal $x(t)$ is defined as

$$WT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) g\left(\frac{t-b}{a}\right) dt \,. \tag{7}$$

As with the Short-time Fourier transform (4), the signal $x(t)$ is transformed by an analyzing function $g\left(\frac{t-b}{a}\right)$, analogous to $w(t-\tau)e^{-j2\pi f t}$ in the STFT.

The analyzing function $g(t)$ is not limited to the complex exponential. In fact, the only restriction on $g(t)$ is that it must be short and oscillatory; i.e. it must have zero average and decay quickly at both ends.[1] This restriction ensures that the integral in (7) is finite and gives the name wavelet or "small wave" to the transform, with $g(t)$ referred to as the "mother wavelet" and its dilates and translates simply as "wavelets". Figure 3 gives examples of two mother wavelets showing their oscillatory and potentially non-sinusoidal nature [5, 6].

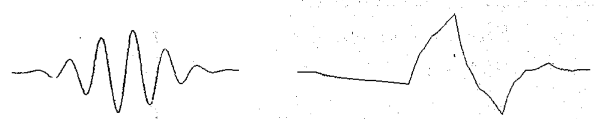


Figure 3: Example mother wavelets.

The second difference is the time-scaling parameter, a, not present in the STFT. The time extent of the wavelet $g(\frac{t-b}{a})$ is expanded or contracted in time depending on whether $a > 1$ or $a < 1$. A value of $a > 1$ ($a < 1$) expands (contracts) $g(t)$ in time and decreases (increases) the frequency of the oscillations in $g\left(\frac{t-b}{a}\right)$. Hence, as a is ranged over some interval, usually beginning with unity and increasing, the input is analyzed by an increasingly dilated function that is becoming less and less focused in time.

As with the STFT, the wavelet transform has a digitally implementable counterpart the *Discrete Wavelet Transform* (DWT). The DWT is defined as

$$DWT[m,k] = \frac{1}{\sqrt{a_0^m}} \sum_n x[n] g\left[\frac{k - n a_0^m}{a_0^m}\right] \tag{8}$$

where $g[n]$ is the mother wavelet, and the scaling and translation parameters a and b of (7) are functions of an integer parameter m, $a = a_0^m$ and $b = n a_0^m$. The result is geometric scaling, i.e. $1, \frac{1}{a}, \frac{1}{a^2}, \ldots$, and translation by $0, n, 2n, \ldots$. This scaling gives the DWT logarithmic frequency coverage in contrast to the uniform frequency coverage of the STFT as compared in Figure 4.

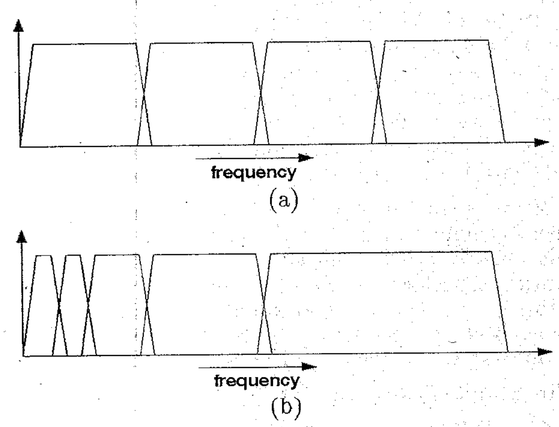
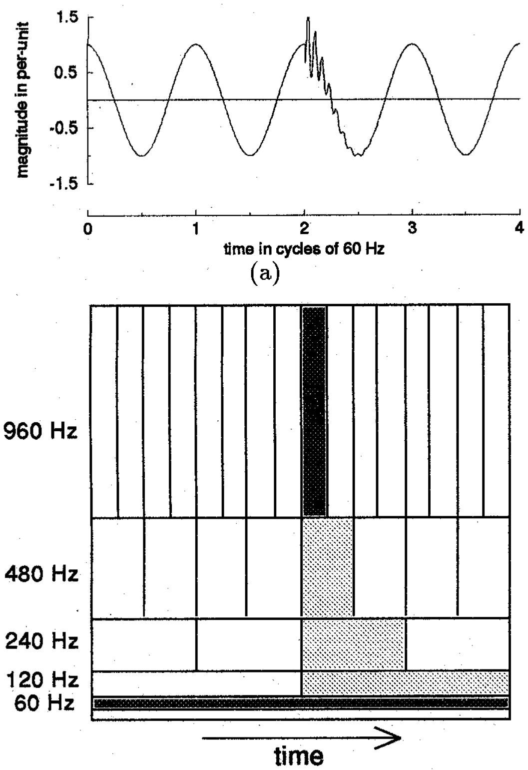


Figure 4: Comparison of (a) the windowed-DFT uniform frequency coverage to (b) the logarithmic coverage of the DWT.

The DWT output can be represented in a two-dimensional grid in a similar manner as the STFT but with very different divisions in time and frequency as shown in Figure 5(b) for the signal of Figure 5(a). The rectangles in Figure 5(b) have equal area or constant time-bandwidth product such that they narrow at the lower scales (higher frequencies) and widen at the higher

[1] Note that the restriction on $g(t)$ is not very severe and that an infinite number of such functions exists.



(b)

Figure 5: Discrete wavelet transform output: (a) example input signal, (b) *DWT* on input signal.

scales (lower frequencies) and are shaded proportionally to the magnitude of the DWT output for the input signal.

In contrast with the WDFT for identical input (shown in Figure 2), the DWT isolates the transient component in the top frequency band at precisely the quarter-cycle of its occurrence while the 60 Hz component is represented as a continuous magnitude. This illustrates how the multi-resolution properties of the wavelet transform are well suited to transient signals superimposed on a continuous fundamental.

Implementation of Wavelets

Observation of the structure of (8) suggests an efficient filter bank implementation of the wavelet transform, as shown in Figure 6. With the variable swap of k for n, (8) can be rewritten

$$DWT\,[m,n] = \frac{1}{\sqrt{a_0^m}} \sum_k x\,[k]\, g\left[a_0^{-m} n - k\right] \qquad (9)$$

to show the similarity of (9) to the general equation for Finite Impulse Response (FIR) digital filters [4],

$$y\,[n] = \frac{1}{c} \sum_k x\,[k]\, h\,[n-k] \ . \qquad (10)$$

This suggests that $g\left[a_0^{-m} n - k\right]$ is the impulse response of a low-pass digital filter with transfer function $G(\omega)$ [7, 8]. Then by selecting $a_0 = 2$, or $a_0^{-m} = 1, \frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \ldots$, each dilation of $g\,[n]$ effectively halves the bandwidth of $G(\omega)$.

The multi-stage filter bank shown in Figure 6 implements the DWT using the low-pass mother wavelet $g\,[n]$ and its high-pass dual $h\,[n]$.[2] Downsampling ($2\downarrow$) at the output of the low-pass filter $g\,[n]$ effectively scales the wavelet by two for the next stage.

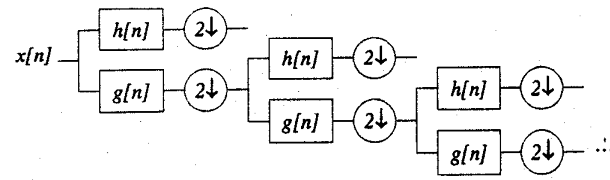


Figure 6: Multi-stage filter bank DWT implementation.

If the mother wavelet on which $g\,[n]$ and $h\,[n]$ are based is constrained to those forming an orthonormal basis [6], this implementation has the property that its output is unique. Uniqueness is exploited in data compression schemes for voice and video and can be applied to power system transients. The digital implementation of DWT using a filter bank is also computationally efficient [7]. Figure 5 showed output of this implementation.

The above filter bank implementation is sensitive to translations of the input [9]. For example, the output can differ dramatically depending on when a transient occurs in the 60 Hz cycle and relative to the boundaries of the wavelet windows. If the application can tolerate non-uniqueness in the output, as in the case of feature detection strategies, the downsampling at each filter output is omitted and the filters scaled by two in each stage as shown in Figure 7. The output is independent of the time location of the transient and retains the multiresolution properties of the DWT.

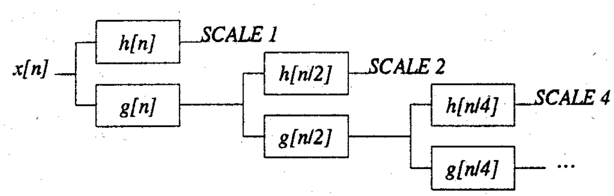


Figure 7: Translation independent implementation of the DWT.

Any valid wavelet can be used in this implementation, though certain wavelets, such as those described in [10], generate symmetric filter coefficients for linear phase shift and other desirable properties.

APPLICATIONS OF WAVELETS

Wavelets can be used as an aid to the detection of features in transient signals to facilitate both manual and automated analysis. The task of sorting and diagnosing transient events by manual inspection can be improved by the use of wavelets as a transient signal preprocessing tool. Certain of these features can also be captured by software to provide a feature detection strategy for an automated transient signature recognition system. In the following we discuss the advantages of applying wavelets

[2] The coefficients of filter $h\,[n]$ are the reverse of $g\,[n]$ with every other coefficient negated.

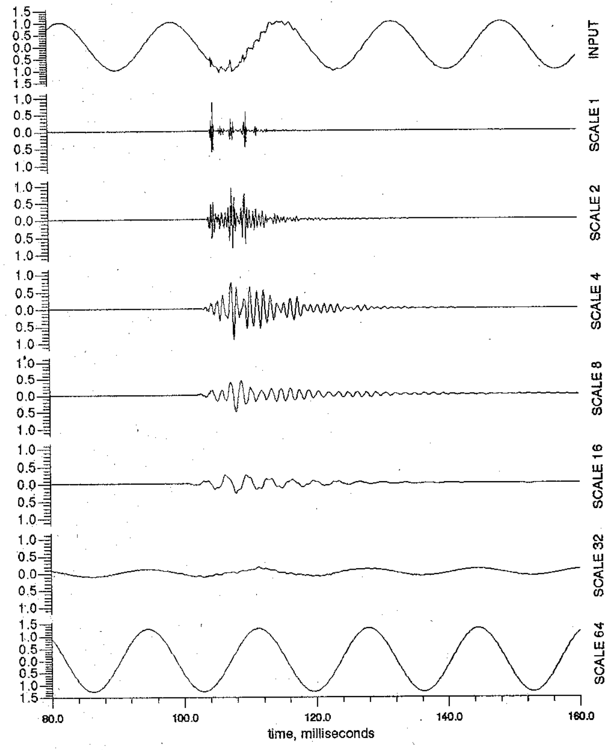


Figure 8: DWT of the phase-A voltage of a three-phase transmission capacitor switching transient obtained by EMTP simulation.

to transient signals for both manual and automated analyses.

Wavelets for Power System Transients

The wavelet transform is particularly appropriate for power system transients since it partitions the frequency spectrum according to identifiable frequencies as illustrated in the following example.

The output of the Figure 7 implementation is a multi-signal trace from each high-pass filter $h[n]$, corresponding to a particular scale parameter, a_o^m =SCALE 2^m, as shown in Figure 8. The input signal, one phase voltage of a three-phase transmission line capacitor switching transient, is plotted in the top trace of Figure 8. The traces labeled SCALE 1, SCALE 2, SCALE 4, ..., in this figure correspond to the filter outputs $h[n]$, $h[n/2]$, $h[n/4]$, ..., of Figure 7. Each trace is a signal appearing at the filter output at the same sample rate as the input.

The particular wavelet scaling and sample rate used to generate the output of Figure 8 provides a meaningful decomposition of the transient into distinct power system signal phenomena. Assuming a 10-kHz sample rate and scaling by two ($a_o = 2$), the chart of Figure 9 shows the association of each SCALE 2^m with a frequency band containing distinct components of power system signals. This scheme can also apply to signals with higher and lower sample rates, doubling or halving the 10 kHz rate to get the decomposition shown.

With Figure 9 as a reference to the output in Figure 8, the highest frequency impulse components appear in SCALE 1. In successive scales, the relative amount of energy in each frequency band is shown by the magnitude and duration of the oscillations. The bulk of energy in the transient appears in SCALE 4, the 625 Hz

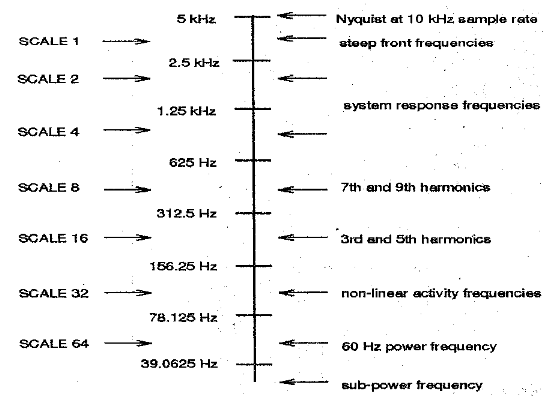


Figure 9: Wavelet decomposition for power system transients sampled at 10 kHz, scaling parameter of two, showing association of scale to components of the transient signal.

to 1.25 kHz frequency band. The transient energy is filtered through successive stages until only the underlying fundamental at 60 Hz remains in SCALE 64. No subharmonics were considered in the model generating the input data, though further wavelet processing would reveal lower half-band components if present.

Feature Analysis

A closer look at the SCALE 1 trace of Figure 8 reveals three bursts in the first quarter-cycle of the transient event. The closing time of the phase-A capacitor bank is shown by the first impulse in this trace. Two successive impulses show the effect of the closings of the phase-B and phase-C banks. The observation that three such bursts occurred in close succession may be enough to suggest that such an input signal of unknown origin was, in fact, a capacitor switching transient as opposed to some other type of transient disturbance.

The distribution of energy in a capacitor switching transient as compared to a fault-type transient can be seen by comparison of wavelets outputs. The top trace of Figure 10 is the phase-A voltage of a capacitor switching transient on an actual distribution system. The remaining traces are the wavelet SCALE outputs as in Figure 9. A single-phase fault on the same distribution system is shown in the top trace of Figure 11 along with its resulting wavelet analysis. It is interesting to note that the dominance of the fundamental 60-Hz component makes the actual waveforms appear more similar than different. The application of the wavelet transform, however, reveals that each waveform has distinct features. In the case of the relatively fast capacitor switching, only the highest frequency (lowest scale) modes are excited, and the oscillation or ringing in SCALE 4 may be at a natural frequency that is affected significantly by the switched capacitors. For the fault, in which the phase-B voltage is essentially driven to zero for more than a quarter cycle (not shown), a broader band of frequencies is coupled to the phase-A voltage as shown in Figure 11.

Automated Feature Detection

Automated recognition means determining what type of disturbance caused a captured transient to occur using

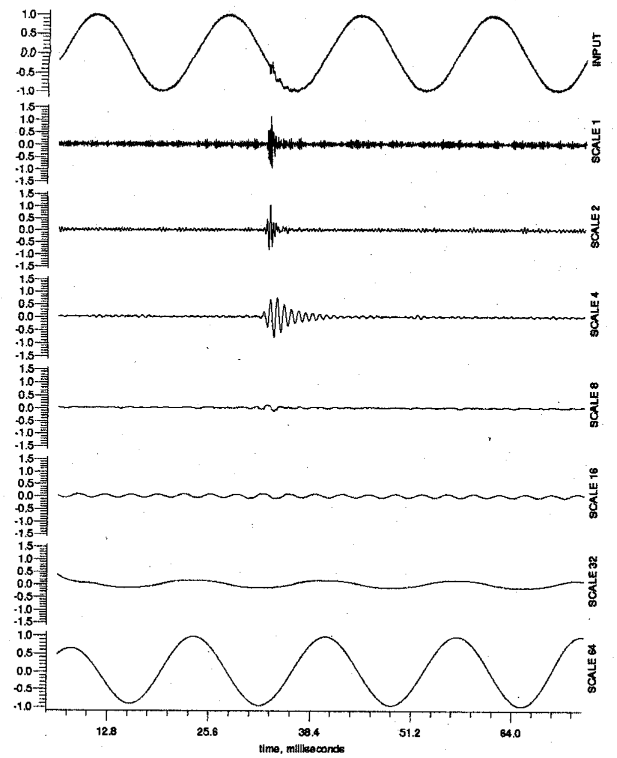


Figure 10: Wavelet transform of phase-A voltage of distribution primary during a recorded capacitor switching transient.

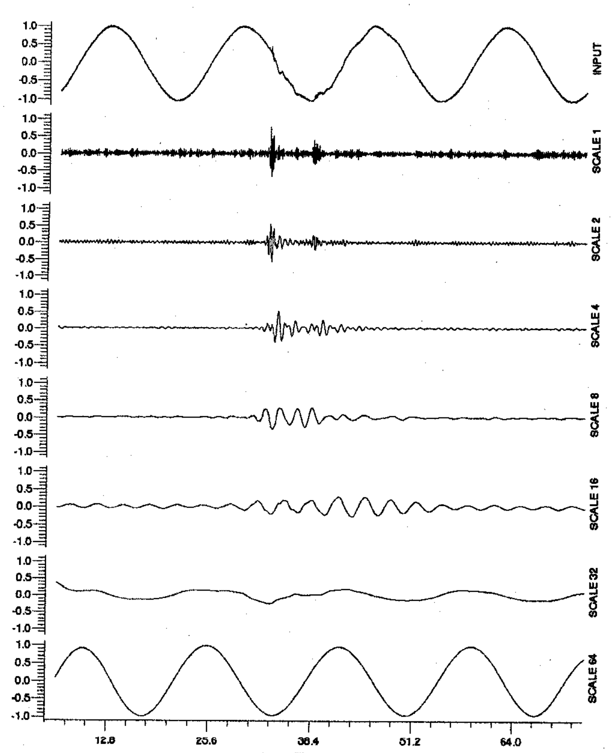


Figure 11: Wavelet transform of phase-A voltage of distribution primary during a recorded single-phase fault on phase B.

features in the waveform signature. Benefits to this extension of the visual analysis capability described above include:

- *Selective capture and waveform storage* - A transient recorder programmed to classify transients by type and to store only "interesting" transients, recorder could keep fault-type transients and discard capacitor bank switching transients. This would increase the transient data's usefulness to the power engineer.

- *Centralized transient disturbance reporting* - Existing data communications facilities can be used for automated reporting of detected transients by reducing transient waveforms to an information packet containing disturbance type and critical parameters. Developments in sophisticated control systems such as FACTS [11] can use such information to actively monitor the system.

- *Incipient failure detection* - Incipient failures of transformer windings, for example, can be detected through fixed installations of transient recorders with more sensitive triggers and a recognition system to identify the characteristic signals of these failures.

- *Power quality conflict resolution* - Classification of transients can be used to identify the cause and source of problems at a utility-industrial interface. The use of selective storage would reduce the data analysis burden, maximizing the probability of capturing the offending transient activity.

The goal in each of the above is to reduce the large volume of transient signal data to a much smaller and higher quality information packet to archive or actively distribute to the power system. The result is to enhance the value of transient data from digital recording equipment through increased use of day-to-day transient event monitoring.

A small-scale demonstration system for recognition of power system transients has been published in [12]. Using simulated EMTP data from a 1000 MVA transmission line model, two types of transients, capacitor switching and single-phase fault, the system accurately distinguished between the two types and identified the location of the disturbance on either of two buses distanced 100 miles apart. This preliminary study showed the potential for wavelets in the design of transient recognition systems.

CONCLUSIONS

This paper introduced the use of the wavelet transform for the analysis of electromagnetic power system transients. The property of multiresolution in time and frequency provided by wavelets allows accurate time location of transient components while simultaneously retaining information about the fundamental frequency and its low-order harmonics. This property of the wavelet transform facilitates the detection of physically relevant features in transient signals to characterize the source of the transient or the state of the post-disturbance system. Furthermore, this capability can be used in the design of automated transient classification systems.

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Discussion

A. W. Galli, G. T. Heydt (Center for the Advanced Control of Energy and Power systems, Purdue University, W. Lafayette, IN). This paper is a thorough discussion and proposal of the use of a multiresolution method in time and frequency to identify and analyze power system transients. This is a timely topic that has been applied in signal processing, and may have a considerable impact on power engineering. The proposal is to use the wavelet transform for this application. The first proposal to use wavelets in power engineering is often credited to Ribeiro [1]. We presented an overview in [2]. However, the present paper differs from earlier works in that a specific application is proposed and the details are given on how features of transients can be extracted using wavelets. Four different specific application areas are descried: selective capture of waveforms for event recorders; disturbance classification and reporting; incipient failure detection; and analysis for power quality problem resolution. The paper is carefully written and indicates a depth of knowledge of the subject.

Our work using wavelets and the wavelet transform has focused more on transient waveform analysis. We have found that the many parameters that surround the wavelet transform have a strong bearing on the success of the method. Some of these choices are: the type of wavelet; the scaling factor, a_0 , in Equation (8); the range of summation in Equation (8); and the ranges of shift, k, and dilation, m, to be considered. To expand on this point further, for example, the resolution in time must be such that the event is captured properly. In some cases, smaller time resolution might not yield better results because certain portions of the event may not be 'positioned' properly with respect to the discrete wavelet components. Similarly, the resolution in the dilation axis is important to overall accuracy. Did the authors also observe these sensitivities? If so, can guidelines on 'tuning' the wavelet transform be given? The choice of the mother wavelet is crucial in these applications. We agree with the authors' basic selection, but there are many other functional forms of even this type of wavelet. Can the authors describe further how the mother wavelet is to be selected and, once the basic format is selected, how the mathematical form and the scale factor, a_0, shown in Equation (8) is determined. The ambiguity of wavelet type is a clear disadvantage of the method. Would a 'library' of mother wavelets be useful for practical applications?

The subject of exponential spacing as shown in Figure (4) is well explained in the paper. Could the authors comment on the optimality of this choice of spacing? It appears that other techniques could be used to space dilated wavelets farther and farther apart as m increases. But would these alternative methods give better results for fewer terms in the inverse wavelet transform? A related point deals with the factor $\frac{1}{\sqrt{a_0^m}}$ in Equation (8). Does this normalization factor depend on the functional form of g(n)?

The application areas opened by the authors are really classification techniques. The paper shows the value of the wavelet approach in classification of disturbances. However, the subject of the analysis of the disturbances and their propagation are less evident. Could the authors explain further the proposal of incipient failure detection? We feel that there is a great deal of work to be done in analytical techniques using the wavelet transform. This could lead to a better method of analyzing transient propagation. The area of incipient fault detection, especially when only measurements far from the location of the incipient fault are available, could benefit from the wavelet approach. Any comments by the authors would be appreciated.

Finally, could the authors describe the software used in the reported studies.

[1] Paulo F. Ribeiro, "Wavelet Transform: An Advanced Tool For Analyzing Non-Stationary Harmonic Distortions in Power Systems," *Proceedings IEEE ICHPS VI.* Bologna, Italy. September 21-23,1994. pp. 365-369.

[2] A. W. Galli, "The Wavelet Transform for Power Quality Assessment," Student Paper Poster Session 1995 IEEE Power Engineering Society Winter Meeting, New York City, February 2, 1995.

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D. Robertson, J. S. Mayer, O. I. Camps, and W. B. Gish:

Several of the issues raised by this discussion were omitted from this paper for reasons of limited space and to remain focused on one facet of the work. We thank the discussors for their comments and questions and, in response, the opportunity to discuss some additional details of our experience with wavelets and power system transient analysis.

As part of a larger work, our research into wavelets for power system transients analysis showed that a feature detection strategy based on wavelets could lead to a successful transients classifier [1]. Further research into the precise nature and choice of wavelet parameters, as the discussors suggest, would indeed benefit this and other applications of wavelets.

For our work, the choice of wavelet and wavelet parameters hinged on the following goals:

1) discrimination between different types of transient disturbances;
2) time-localization of the transient event;
3) independence from time-of-event relative to phase angle of the power frequency;
4) linearity in phase-angle over a wide frequency range;
5) computationally feasible in software or DSP hardware.

Several sensitivity analyses were conducted which impacted the choice of wavelet and its parameterization. Using transient simulation and varying the time of the transient (capacitor switch closure and fault application times), the amount of load and power factor, we analyzed the phase- and zero-sequence voltage and current signals with a variety of orthogonal and non-orthogonal wavelets. Specifically, we experimented with Haar, Daubecies, Coiflets, and B-spline wavelets of varying length. We then pursued progressively more effective non-orthogonal wavelets beginning with Haar, in a non-orthogonal implementation [2], and arriving at a set of linear-phase FIR, quadratic wavelet filters [3].

Analysis by orthogonal wavelets showed little hope for achieving good time localization or time-of-event independence. We then experimented with non-orthogonal mother wavelets, using dyadic scaling for computational efficiency, but with translation of the wavelets in single-point steps (k=1). The higher-order Feauveau wavelets used in a dyadic scale, multistage FIR filter bank (see Figure 7 in paper) were found to meet the discrimination, computation, independence, and linearity goals stated above.

In response to the discussors interest in finding the best wavelets for power system transients, we believe that the choice of wavelet must be guided by the application. Clearly, the application of wavelets to data compression, feature detection, and wave propagation require quite different wavelets and wavelet parameters.

An approach and tools for selecting the mother wavelet *and the implementation strategy* for power system transients would be far more useful than a definitive set of wavelets. Selection of a library of wavelets with an algorithm to find this library along the lines of the "Matched Pursuit" algorithm [4] would certainly be a good starting point.

The exponential spacing shown in Figure 4b. of the paper is a direct consequence of dyadic scaling; the bandwidth of the mother wavelet is halved at each scaling and then applied to the approximation or remainder of the signal (see Figure 6). This again was desirable for a computationally feasible implementation. The exponential spacing depicted in Figure 4b. is perhaps the one unifying concept of multiresolution transforms, whether scaling by 1.001 or exactly two.

If we understand the discussors question on the spacing optimality of dilated wavelets we would have only one comment. Achieving fewer terms in the inverse wavelet transform using more optimal wavelets and spacing techniques would help both compression (fewer terms) and feature detection (fewer features, each with more information). Although unsure how the normalization factor ($1/\sqrt{a_0^m}$) in equation (8) relates to the discussors question, this factor maintains constant energy in the scaled wavelet and is independent of the functional form of g[n].

Incipient failure detection as envisioned by the authors is the detection of signature signals typical of soon-to-fail power system components. Wavelets helps in two ways: 1) by robust classification techniques, instrumentation can be set more sensitively and thus capture minor transients without data overload, and 2) better information can be extracted from the failure signature.

The software used in the reported study was based on the "Wavel" program described in [2] with the enhancement of Feauveau's quadratic wavelet filters.

Additional references:

[1] D. Robertson, O. I. Camps, and J. S. Mayer. "Wavelets and power system transients: feature detection and classification" in *SPIE International Symposium on Optical Engineering in Aerospace Sensing*, vol. 2242, pp. 474--87, April 1994.

[2] S. Mallat and W. L. Liang. "Singularity detection and processing with wavelets" in *IEEE Transactions on Information Theory*, vol. 38, no. 2, pp. 617-643, March, 1992.

[3] Jean-Christophe Feauveau. "Non-orthogonal multiresolution analysis using wavelets" in Charles K. Chui, editor, *Wavelets: A Tutorial in Theory and Applications*, vol. 2, pp. 153--177. Academic Press, New York, 1992.

[4] S. Mallat and S. Zhang, "Matching Pursuit with Time Frequency Dictionaries" in *IEEE Transactions in Signal Processing*, December 1993.

Manuscript received October 13, 1995.