Wavelet-Based Signal Processing Techniques
For Disturbance Classification and Measurement

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Abstract:
This paper presents the wavelet domain theoretical basis for rms value and total harmonic distortion measurements. It provides a systematic method for analyzing power system disturbances in the wavelet domain. The wavelet domain capabilities in detection, classification, and measurements of different power system disturbances are presented. The distortion event is mapped into the wavelet domain and extracted from the measured signal. The duration of the distortion is measured in a noisy environment and its energy and rms value is also evaluated. The proposed algorithm is applied for different power system disturbances.

Indexing terms: Electric disturbances, wavelet analysis, multi-resolution signal decomposition, and feature extraction

I- Introduction

Automatic Data Processing (ADP), sensitive microprocessor, and power electronic equipment are installed to control and automate different assembly lines. However, due to growing economic pressure, modern electrical equipment are designed to meet their operating limits. This fact means that different equipment manufacturers face a dual responsibility to both desensitize and protect their equipment. This incompatibility issue, between power system disturbances and immunity of equipment, results in a severe impact on the industrial processes. This emphasizes the need for a powerful automated monitoring system that can help manufacturers in identifying the gap between different disturbances and equipment susceptibility. The era of deregulation, furthermore, pushes electric utilities and customers to identify a baseline for their electric quality levels for different complex dynamic systems [1-6].

The automatic management of such dynamic systems, controlled by sensitive equipment installed in a polluted electric environment with disturbances that may overlap in time and frequency, requires a wide-scale power quality monitoring system with special characteristics. Some of these characteristics are:

- Fast detection and localization of disturbances that may overlap in time and frequency in a noisy environment.
- On-line classification by extracting discriminative, translation invariant features with small dimensionality can represent efficiently the voluminous size of distorted data.
- Analysis of different disturbances and measurement of its power quality indices.
- De-noising ability and high efficiency in data compression and storing.

This automated monitoring system with these characteristics can be achieved in a wavelet domain.

This paper proposes a procedure that will assist in the automated detecting, classifying, and measuring of different power system disturbances. The paper also presents a new technique that can monitor the variations of the rms value and any further changes in the signal during the distortion event. The wavelet domain theoretical basis for rms value and total harmonic distortion measurements is presented. The distortion event \( s(t) \) is mapped into the wavelet domain and extracted from the raw data. The duration of the distortion is measured in a noisy environment. The distortion event is classified and its energy and rms value is measured. The proposed algorithm is applied on different simulated disturbances.

The paper is organized as follows. A general review of the applications of wavelet transform to power systems is presented in section II. Section III presents the mathematical formulation of the mapping process to the wavelet domain. A systematic method for analyzing power system disturbances in wavelet domain is presented in this section. The distortion coefficients are extracted and the noise level is measured. Distortion detection and feature extraction are also discussed in this section. The non-rectangular rms variation during a distortion event is also presented in this section. The distortion is analyzed and
its indices are presented. Application of the monitoring tool proposed to assist in automated detecting, classifying, and measuring different power system disturbances is presented in section IV. The conclusion and references are given in sections V and VI.

II- Review of Wavelet Applications in Power Systems

Wavelets have been successively applied in a wide variety of research areas such as signal analysis, image processing, data compression and de-noising, and numerical solution of differential equations. The wavelets’ power comes from their location at the crossroads of a wide variety of research areas. Recently, wavelet analysis techniques have been proposed extensively in the literature as a new tool for monitoring and analyzing different power system disturbances. Other researchers proposed wavelet analysis as a new tool in different power engineering areas. The following section summarizes some of the previous work of applying wavelets in a power system, with emphases on power quality and transient analysis areas.

- **Detection, Localization and Classification**

  Wavelet multi-resolution signal decomposition was applied to detect and localize different power quality problems. The squared wavelet coefficients were used to find a unique feature for different power quality problems. It was proposed that a proper classification tool might then be used depending on the unique feature to classify different power quality problems [7]. In [8] multi-resolution analysis was proposed as a new tool that may be used to detect different disturbances, or to present the state of post-disturbances, and to identify their sources. In [9] a combination of wavelet and neural net was implemented to classify a one-dimensional signals embedded in normally distributed white noise. Noise signals were decomposed using The Haar wavelet basis and Daubechies 4 wavelet. A feed forward neural network was trained on wavelet series coefficients at various scales and the classification accuracy for both wavelet bases was compared over multiple scales, several signal-to-noise ratios, and varying numbers of training epochs. In [10] a wavelet transform approach, using Morlet basis, was applied to detect and localize different kinds of power system disturbances. However, it could not be easily used to discriminate among different power quality problems. In [11] the wavelet transform and multi-resolution signal decomposition were used to extract important information from the distorted signals. The distribution of the distorted signal energy at different resolution levels is proposed to present simple classification roles for the operator to detect, localize, and classify different power quality problems.

- **Measurements**

  In [12] a new technique was proposed to detect, localize, and estimate automatically the most relevant disturbances in power systems. The proposed method combines the use of continuous wavelet transform, modulus maxima properties, multi-resolution signal decomposition, and reconstruction by means of discrete-time wavelet transform. In [13] a wavelet-based algorithm was used to measure the power and rms values of a harmonic distorted signal. The algorithm was applied on simulated and actual sets of periodic data. Frequency separation into the various wavelet levels was discussed using IIR and FIR filters. The results were compared with that derived by using Fourier Transform. In [14] the distribution of the distorted signal energy at different resolution levels was used as a features to localize, detect, and classify different disturbances. Furthermore, these features were used to measure the magnitude of the signal during short duration variations within the power systems.

- **Data Compression**

  In [15] wavelet transformation was applied as a compression tool for power system disturbances. Three simulated transient voltages were generated and reconstructed by using a suitable mother wavelet and by using only 2% of the coefficients. This approach presented the efficiency of wavelet transform to reconstruct non-stationary power system disturbances. In [16] the arc furnace current was decomposed into a series of 11 wavelet levels. A good approximation to the original waveform was obtained by adding only five of the wavelet levels. In [17] wavelet analysis was applied to compress actual power quality data and the compression ratio achieved was in the range of 3-6 with normalized mean square errors of the order of $10^{-16}$ to $10^{-5}$. In [18] power system disturbances compression results using the discrete wavelet transform and wavelet packet were presented. The wavelet transform offered compression ratios $\leq 10:1$ compared to that by the discrete cosine transform.

- **Transient Analysis**

  In [19] the wavelet technique was proposed for analyzing the propagation of transients in power systems. The approach concluded that it is possible to use wavelets to calculate the transient within the system. The advantage of the method depends on the similarity of the existing transient to the selected mother wavelet. The wavelet transform was used to solve the differential equations as an example of the use of multi-resolution analysis. In [20] Daubechies wavelets have been used for the analysis of power system transients. The method is based on the wavelet companion equivalent circuit of power
system components, such as resistors, inductors, capacitors, and distributed parameter lines. This equivalent circuit is developed by applying the wavelet transform on the integral-differential equations of the power system elements.

- **System Protection**

In [21] wavelets were introduced in the power system-relaying domain. It was shown that wavelet may be employed for analyzing recorded data to study efficiently the faulted network. It was proposed to implement the wavelet transform in real-time protection devices. The information of the transient period analyzed by wavelet can help to improve the performance of the protection system. In [22] wavelet transform was applied to identify the fault location in transmission systems. The wavelet transform was used to extract the traveling time information accurately for signals traveling between the faulted point and the line terminals. The first two levels of high frequency wavelet transform coefficients were shown to carry information directly related to the location of the transmission line fault. This information was then used to find the location of the fault.

### III- Mapping Into Wavelet Domain

Assume a finite length signal with additive distortion of the form:

\[
f(t) = p(t) + S(t)
\]  

Applying multi-resolution analysis, one can decompose the signal \( f(t) \) at different resolution levels and present it as a series expansion by using a combination of scaling functions \( \phi_k(t) \) and wavelet functions \( \psi_k(t) \). This can be mathematically presented as:

\[
f(t) = \sum_{k} c_k(0) \phi(t - k) + \sum_{j=0}^{J-1} \sum_{k} d_j(k) 2^{j/2} \psi(2^j t - k)
\]  

where, \( J \) represents the total number of resolution levels and \( c_j(k) \) is the set of scaling function coefficients and \( d_j(k) \) is the set of wavelet function coefficients. For an orthonormal basis, the set of expansion coefficients \( \{c_j(k) \text{ and } d_j(k)\} \) can be calculated using the inner product:

\[
c_{j-1}(k) = (f(t), \phi_{j,k}(t)) = \sum_{m} h(m - 2k) c_j(m)
\]  

\[
d_{j-1}(k) = (f(t), \psi_{j,k}(t)) = \sum_{m} h_1(m - 2k) c_j(m)
\]  

where \( h(k) \) and \( h_1(k) \) present the scaling and wavelet functions coefficients respectively. The wavelet function coefficients are related, by orthogonality, to the scaling function coefficients by the following relation:

\[
h_1(k) = (-1)^k h(1-k)
\]  

The input set of the scaling coefficients \( c_j(k) \) is obtained from the signal. If the samples of the signal \( f(t) \) are above the Nyquist rate, then they are good approximations to the scaling coefficients at that scale. This means that no wavelet coefficients are necessary at that scale [23].

In wavelet domain, using (3) and (4), the wavelet coefficients that represent the distorted signal \( f(t) \) at different resolution levels are:

\[
C_{Signal} = [c_o \mid d_0 \mid d_1 \mid \ldots \mid d_{J-1}]
\]  

where \( J \) represents the total number of resolution levels.

A set of discriminative, translation invariant features with small dimensionality that present the energy distribution of \( f(t) \) at different resolution levels, can be presented by computing the norm of the \( C_{Signal} \), as follows:

\[
E_{Signal} = \|c_o\|_2 \|d_0\|_2 \|d_1\|_2 \ldots \|d_{J-1}\|_2
\]  

\[
\|c_o\|_2 = \left( \sum_{k=\infty}^{\infty} |c_o(k)|^2 \right)^{1/2}
\]  

\[
\|d_j\|_2 = \left( \sum_{k=\infty}^{\infty} |d_j(k)|^2 \right)^{1/2}
\]  

In a similar way, the wavelet coefficients of a pure signal \( C_{pure} \) can be generated and used as a reference for the purpose of classification and measurements. These coefficients are:
and their energy distribution can be presented by the norm of the $C_{\text{pure}}$, using (8 and 9):

$$C_{\text{dist}} = C_{\text{Signal}} - C_{\text{pure}}$$

The proposed feature vector $x_o$ that classify the distortion event can be generated by subtracting $E_{\text{pure}}$ from $E_{\text{signal}}$,

$$E_{\Delta} = E_{\text{signal}} - E_{\text{pure}}$$

This feature vector can mathematically be represented as:

$$x_o = \{ \Delta E_{d_0}, \Delta E_{d_1}, \Delta E_{d_1}, \ldots \Delta E_{d_{(J-1)}} \}$$

### a - Distortion Detection and Localization

Any changes in the pattern of the signal can be detected and localized at the finer resolution levels. As far as detection and localization is concerned, the wavelet coefficients of the first finer decomposition level of $f(t)$ are normally adequate to detect and localize any disturbance in the signal. These coefficients are:

$$d_{(J-1)}(k) = \langle f(t), \psi_{(J-1)k}(t) \rangle = \sum_{m} h_{1}(m-2k) c_{j}(m)$$

Since the samples of the distorted signal $f(t)$ are above the Nyquist rate, then the scaling coefficients $c_j$ are presented by the samples of the distorted signal $f(t)$. For a pure signal, the set of coefficients $d_{(J-1)}(k)$ presented in (16) are equal to zero. Any changes in the signal can be detected and localized in time due to the changes in the magnitude of these coefficients. This property is shown in Fig. (1). An impulsive transient event, Fig. 1a, is detected and localized due to the changes in the magnitude of the wavelet coefficients at the first resolution level. However, as the transient event magnitude decreases and the noise level increases, the coefficients that represent the noise will merge with those representing the transient event. This will cause a failure in the wavelet detection and localization property. Fig (2a) shows a harmonic distorted signal where the total harmonic distortion equals to 26.6%. The signal is further distorted with a sag to 0.8 p.u. for one cycle. If the noise level is small then the first resolution level can be used to detect and localize the sag event as shown in Fig (2b). However, as the noise level increases, the first resolution level can no longer detect and localize the transient event, Fig (2c).

A new technique relying on noise level assessment and an approximated version of the distortion event is proposed to de-noise and localize the transient event and to measure its duration, $\Delta \tau$, in a noisy environment.

### b - Noise Level Assessment

In multi-resolution analysis, as shown in Fig. (3), the first stage will divide the spectrum of distortion into a low-pass and high-pass band, resulting in the scaling coefficients and wavelet coefficients at a lower scale $c_{(J-1)j}(k)$ and $d_{(J-1)j}(k)$. The second stage then divides that low-pass band into another lower low-pass band and a band-pass band. The first stage divides the spectrum into two equal parts. The second stage divides the lower halves into quarters and so on.

The noise is defined as an electrical signal with wide-band spectral content lower than 200kHz superimposed upon the distorted signal [3]. Therefore, great part of the noise energy is expected to appear at the highest resolution level $(J-1)$. This means that the energy of the coefficients $\Delta E_{d_{(J-1)}}$ at the highest resolution level can give good indication about the energy of the noise superimposed over the signal. For a pure signal,

$$\Delta E_{d_{(J-1)}} = 0$$

The variation of the $\Delta E_{d_{(J-1)}}$ with different noise levels superimposed on a pure signal is presented in Table (1).

<table>
<thead>
<tr>
<th>Noise</th>
<th>0.0%</th>
<th>0.25%</th>
<th>0.50%</th>
<th>0.75%</th>
<th>1.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta E_{d_{(J-1)}}$</td>
<td>0.0</td>
<td>0.1521</td>
<td>0.3143</td>
<td>0.4646</td>
<td>0.6345</td>
</tr>
</tbody>
</table>

An assessment of the noise level can be determined as the value of $\Delta E_{d_{(J-1)}}$ goes beyond zero or a certain threshold value.
**c - Detection and Localization in a Noisy Environment**

As the noise level increases, \( \Delta E_{d(j-1)} > 0 \), the distortion event can be localized by reconstructing an approximated version of the distorted signal. This can be mathematically represented as:

\[
s(t) = \sum_{k} c_{od}(k)\phi(t - k) + \sum_{k} d_{jd}(k)2^{j/2}\psi(2^{j}t - k) \quad (18)
\]

Fig 1: a- impulsive transient phenomena, b- detection and localization of the transient event at the first resolution level.

Fig 2: a- harmonic distorted signal with one cycle sag to 0.8 phenomena, the highest resolution level of the distorted signal with: b- zero noise level and c- 2.0% noise level.

Fig 3: multi-resolution analysis of a distorted signal.
where $F < J$ and $J$ represents the total number of resolution levels and $F$ represents the subspace index or the highest resolution level to be used to reconstruct $s(t)$. The value of $F$ depends on the noise level content and the energy distribution of the distortion event as indicated in (15). Squaring the distortion event and applying the following thresholds can accomplish further reduction for the existing harmonic.

$$m(t) = \begin{cases} 0 & [s(t)]^2 < \theta \\ 1 & [s(t)]^2 \geq \theta \end{cases}$$  \hspace{1cm} (19)$$

where

$$\theta = \text{std} \{s(t)^2\}$$  \hspace{1cm} (20)$$

Utilizing $m(t)$ the starting time $\tau_{\text{start}}$ and the ending time $\tau_{\text{end}}$ of the disturbance event can be localized. The duration $\Delta \tau$ is measured and used to categorize the disturbance as instantaneous, momentary, or temporary.

$$\Delta \tau = \tau_{\text{end}} - \tau_{\text{start}}$$  \hspace{1cm} (21)$$

**d - Distortion Classification**

Relying on Parseval’s theorem, the energy of $f(t)$ will be partitioned at different resolution levels in different ways depending on the type of the distortion event.

Mapping the data of distortion event $s(t)$ into a wavelet domain is the first step in performing the proposed classification process. The distribution of the distortion energy at different resolution levels is computed to generate a set of translation invariant features with small dimensionality. The term “translation invariant” denotes that the features remain unchanged if the distortion event undergoes a change of position (translation). These features have the property of being able to effectively differentiate between different distortion events.

The proposed feature vector $x_o$ can be mathematically represented as:

$$\begin{bmatrix} x_{o1} \\ x_{o2} \\ \vdots \\ x_{oJ} \end{bmatrix} = \begin{bmatrix} \Delta E_{c(o)} \\ \Delta E_{d(o)} \\ \vdots \\ \Delta E_{d(J-1)} \end{bmatrix} = \begin{bmatrix} \|c_{odj}\|_2 \\ \|d_{adj}\|_2 \\ \vdots \\ \|d_{(J-1)adj}\|_2 \end{bmatrix}$$  \hspace{1cm} (22)$$

$$x_{o1} = \Delta E_{c(o)} = \|c_{odj}\|_2 = \left[ \sum_{k=-\infty}^{\infty} s_{ods(k)}^2 \right]^{1/2}$$  \hspace{1cm} (23)$$

$$x_{oJ} = \Delta E_{d(J)} = \|d_{adj}\|_2 = \left[ \sum_{k=-\infty}^{\infty} s_{adj(k)}^2 \right]^{1/2}$$  \hspace{1cm} (24)$$

Figure 4 shows the difference in energy distribution ($\Delta E$) at different resolution levels for 25 distorted signals with the shown power quality problems.
According to Parseval’s theorem, if the used scaling function and the wavelets form an orthonormal basis, then Parseval’s theorem relates the energy of the distortion in the signal \( s(t) \) to the energy in each of the expansion components and their wavelet coefficients \( C_{\text{dist}} \). This means that the energy of the distortion \( W_{\text{dist}} \) can be represented in terms of the expansion coefficients.

In terms of the wavelet coefficients, the energy of the distortion \( W_{\text{dist}} \) is equal to the square of the norm of the wavelet coefficients \( C_{\text{dist}} \).

\[
W_{\text{dist}} = \| C_{\text{dist}} \|_2^2
\]

where, \( \| C_{\text{dist}} \|_2 \) is the norm of the distortion coefficients and can be mathematically represented as:

\[
\| C_{\text{dist}} \|_2 = \sqrt{\langle C_{\text{dist}}, C_{\text{dist}} \rangle}
\]

\[
\| C_{\text{dist}} \|_2 = \sqrt{\sum_{k=0}^{\infty} |c_{\text{od}}(k)|^2 + \sum_{j=0}^{\infty} \sum_{k=-\infty}^{\infty} |d_{\text{jd}}(k)|^2}^{1/2}
\]

Therefore, the true RMS value of the distortion \( s(t) \) can be calculated using the wavelet coefficients as follows:

\[
\text{RMS}_{s(t)} = \left( \frac{1}{\Delta \tau} \| C_{\text{dist}} \|_2^2 \right)^{1/2}
\]

where \( \Delta \tau \) is the duration of the distortion event measured from the localization process as mentioned in (21).

In terms of the wavelet coefficients, the total harmonic distortion (THD) can be computed as follows:

\[
\text{THD} \% = \frac{\| C_{\text{dist}} \|_2}{\| C_{\text{pure}} \|_2} \times 100 \% \]

where, \( \| C_{\text{pure}} \|_2 \) is the norm of the pure signal.

### f - Non-Rectangular RMS- Variation Measurements

It has been documented in [6] that most distortion rms variations are rectangular in shape and a single magnitude and duration can accurately characterize them. However, there are other rms-variations with non-rectangular shapes. These variations are difficult to characterize because there is no single magnitude and duration that can characterize them, Fig. (5a).

In this section, a new wavelet-based procedure to characterize rms variations is presented as shown in Fig. (6). This procedure can help in assessing the quality of service presented in the distribution systems, the quality of the mitigation devices, and the characteristics of any load during rms variations. It can also give important information about any new variations of the distortion within its period. This information may help in finding the source of the disturbance.

The proposed procedure is summarized in the following points and as shown in Fig. (6):

- Any changes in the pattern of the signal can be detected and localized at the finer resolution levels as presented in Sections (III- a and d). The set of coefficients \( d_{\ell(\ell-1)}(k) \) presented in (16) is used to monitor the number of changes in the signal during the selected window size.

- The distorted signal is segmented into window frames with respect to a fixed time interval as shown in Fig. (5b).
• For each frame, find the wavelet coefficients $C$ and $C_{dist}$, where

$$C_{dist} = C - C_{Ref}$$  \hspace{1cm} (30)$$

and $C_{Ref}$ is a reference wavelet coefficients computed from $C_{pure}$:

$$C_{Ref} = Pk_{new} \ast C_{pure}$$  \hspace{1cm} (31)$$

where $Pk_{new}$ is the peak value of the distortion event. Its initial value is selected to be equal to 1 p.u for a pure signal.

• Using $C_{dist}$, the new $RMS_{s(t)}$ and its peak value ($Pk$) of the distorted signal is estimated.

• Use the energy measure $\Delta E_{Ref}(L_f)$ of the resolution level ($L_f$), that covers the power frequency band, to monitor the direction of variation in the $RMS_{s(t)}$ of the distortion event, as shown in Fig. (5d), where

$$\Delta E_{Ref}(L_f) > 0 \iff \text{increasing in rms value}$$

$$\Delta E_{Ref}(L_f) < 0 \iff \text{decreasing in rms value}$$

and

$$\Delta E_{Ref}(L_f) = E_{signal}(L_f) - Pk_{new} \ast E_{pure}(L_f)$$  \hspace{1cm} (32)$$

• The $Pk_{new}$ value is updated to be used for monitoring the new variation in rms value, if exist, in the second window frame.

$$Pk_{new} = Pk_{new} + T \ast Pk$$  \hspace{1cm} (33)$$

and

$$T = \begin{cases} 
1 & \Delta E_{Ref}(L_f) > 0 \\
0 & \Delta E_{Ref}(L_f) = 0 \\
-1 & \Delta E_{Ref}(L_f) < 0 
\end{cases}$$  \hspace{1cm} (34)$$

• Use the proposed feature vector (15) to classify the type of distortion in the signal.

![](image.png)

Fig 5: RMS variation monitoring
A – Detection and Localization in a Noisy Environment

The proposed method is applied to detect, localize, and estimate the duration of the following power system disturbances with different noise levels:

1. Capacitor-switching phenomenon:

   The signal \( f(t) \), Fig. (7a) and its zoomed version Fig. (7b), is simulated with the capacitor-switching phenomenon distortion. The actual starting time of the distortion is 0.4901 s and the ending time is 0.4926 s. The proposed algorithm in Section (II-c) is used to estimate the time information of the distortion. The distortion event \( s(t) \) is synthesized using the wavelet coefficients \( C_{dist} \) as shown in Fig. (7c). The threshold measure (20) is applied on \( [s(t)]^2 \) and \( m(t) \) is constructed to estimate the time information of the distortion, Fig. (7d) and (7e). Table (2) presents the estimating starting and ending time of the capacitor-switching phenomenon with noise level variation from 0% to 1.2%. It can be seen that the estimated time error is increased considerably as the noise level magnitude goes beyond 1.0%. However, higher values of noise level larger than 1.0% is not normally found in power systems [3].

<table>
<thead>
<tr>
<th>Noise Level</th>
<th>Starting time [s]</th>
<th>Starting error %</th>
<th>Ending time [s]</th>
<th>Ending error %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0%</td>
<td>0.4901</td>
<td>0.0</td>
<td>0.4919</td>
<td>0.1239</td>
</tr>
<tr>
<td>0.5%</td>
<td>0.4901</td>
<td>0.0</td>
<td>0.4919</td>
<td>0.1239</td>
</tr>
<tr>
<td>1.0%</td>
<td>0.4901</td>
<td>0.0</td>
<td>0.4919</td>
<td>0.1239</td>
</tr>
<tr>
<td>1.1%</td>
<td>0.4901</td>
<td>0.0</td>
<td>0.8604</td>
<td>74.671</td>
</tr>
<tr>
<td>1.2%</td>
<td>0.1838</td>
<td>62.490</td>
<td>0.4919</td>
<td>72.961</td>
</tr>
</tbody>
</table>
2. Sag in noisy environment:
The same technique is applied for detecting and localization a one-cycle simulated sag phenomenon, Fig (8a). The simulated signal is further distorted with harmonic and has a high noise level. The actual starting time of the distortion is 0.4917 s and the ending time is 0.5083 s. Due to the high noise level, 1.0%, the first resolution level $D_1$, Fig. (8b), can no longer detect and localize the distortion event. The distortion event $s(t)$ is synthesized ignoring the high resolution level, $F = 9$ and $J = 13$, for de-noising purposes, Fig. (8c). The threshold measure (20) is applied on $[s(t)]^2$ and $m(t)$ is constructed to estimate the time information of the distortion, Fig. (8d) and (e). Table (3) presents the estimating rms value and starting and ending time of a sag phenomenon with noise level variation from 0% to 2.0%.

![Image of graphs showing a capacitor-switching phenomenon in a noisy environment](image)

Fig. 7: detection and localization of a capacitor-switching phenomenon in a noisy environment

<table>
<thead>
<tr>
<th>Noise Level</th>
<th>Derived Sag (rms)</th>
<th>Error %</th>
<th>Derived Starting (s)</th>
<th>Error %</th>
<th>Derived Ending (s)</th>
<th>Error %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00%</td>
<td>0.1798</td>
<td>0.0150</td>
<td>0.4921</td>
<td>0.0745</td>
<td>0.5082</td>
<td>0.0240</td>
</tr>
<tr>
<td>0.25%</td>
<td>0.1814</td>
<td>0.0240</td>
<td>0.4921</td>
<td>0.0745</td>
<td>0.5081</td>
<td>0.0480</td>
</tr>
<tr>
<td>0.50%</td>
<td>0.1840</td>
<td>0.0384</td>
<td>0.4921</td>
<td>0.0745</td>
<td>0.5082</td>
<td>0.0240</td>
</tr>
<tr>
<td>0.75%</td>
<td>0.1895</td>
<td>0.0706</td>
<td>0.4921</td>
<td>0.0745</td>
<td>0.5082</td>
<td>0.0240</td>
</tr>
<tr>
<td>1.00%</td>
<td>0.1954</td>
<td>0.1014</td>
<td>0.4921</td>
<td>0.0745</td>
<td>0.5082</td>
<td>0.0240</td>
</tr>
<tr>
<td>1.25%</td>
<td>0.2058</td>
<td>0.1622</td>
<td>0.4922</td>
<td>0.0993</td>
<td>0.5082</td>
<td>0.0240</td>
</tr>
<tr>
<td>1.50%</td>
<td>0.2179</td>
<td>0.2331</td>
<td>0.4921</td>
<td>0.0745</td>
<td>0.5081</td>
<td>0.0480</td>
</tr>
<tr>
<td>1.75%</td>
<td>0.2284</td>
<td>0.2926</td>
<td>0.4921</td>
<td>0.0745</td>
<td>0.5081</td>
<td>0.0480</td>
</tr>
<tr>
<td>2.00%</td>
<td>0.2382</td>
<td>0.3400</td>
<td>0.4922</td>
<td>0.0993</td>
<td>0.5082</td>
<td>0.0240</td>
</tr>
</tbody>
</table>
B - Feature extraction of a transient event
The proposed feature extraction technique is applied on the distorted signal $f(t)$ in Fig. 8a (capacitor switching phenomena). The energy distribution for both the distorted signal (dashed line) and pure one (solid line) is shown in Fig. 8c. The extracted feature vector for $f(t)$ is shown in Fig. 8d. The distorted signal is sampled at 165kHz (8266 sampling points) and mapped into small size feature vector (13 numbers). This feature vector extracts the energy of the distortion event and distributes it on different resolution levels. Fig. 8b shows that the distortion event energy is distributed on resolution levels 1 to 8. Most of the distortion energy is concentrated on the 7th resolution level (645–1289 Hz). The time information of this distortion event is measured from the first resolution level and found to be 7 ms as shown in Fig. 5a. These results; resolution level = 7, frequency band = 645-1289 Hz, and duration = 7ms, are compared with the categories of electromagnetic phenomena presented by IEEE Std.1159 and shown in Table 4. The distortion event is then classified as oscillatory transient with low frequency content.
**Table 4: Typical characteristics of transient phenomena in power systems (Part of Table 2-IEEE Std.1159-1995)**

<table>
<thead>
<tr>
<th>A – Impulsive Transient</th>
<th>Typical Spectral Duration</th>
<th>Typical Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 – Nanosecond</td>
<td>5ns rise</td>
<td>&lt; 50 ns</td>
</tr>
<tr>
<td>2 – Microsecond</td>
<td>1 us rise</td>
<td>50ns - 1 ms</td>
</tr>
<tr>
<td>3 – Millisecond</td>
<td>0.1 ms rise</td>
<td>&lt; 1 ms</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B – Oscillatory Transient</th>
<th>Low Frequency</th>
<th>Medium Freq.</th>
<th>High Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 – Low Frequency</td>
<td>&lt; 5 kHz</td>
<td>0.3-50 s</td>
<td>0-4 pu</td>
</tr>
<tr>
<td>2 – Medium Freq.</td>
<td>5-500 kHz</td>
<td>20us</td>
<td>0-8 pu</td>
</tr>
<tr>
<td>3 – High Frequency</td>
<td>0.5 - 5 MHz</td>
<td>5 us</td>
<td>0-4 pu</td>
</tr>
</tbody>
</table>

**C – Non-Rectangular rms- variation measurements**

A 21-cycle distorted signal $f(t)$ is simulated. This signal undergoes six variations in its magnitude and duration. The distorted signal is segmented into 3-cycle window frames. The feature extracted from each window frame is used to classify the type of distortion. The energy distribution $\Delta E(L_f)$ is used to classify the distortion event as:

$$\Delta E(L_f) < 0 \iff E_{signal}(L_f) < E_{Pure}(L_f) \iff \text{Sag}$$
$$\Delta E(L_f) > 0 \iff E_{signal}(L_f) > E_{Pure}(L_f) \iff \text{Swell}$$
$$\Delta E(L_f) = 0 \iff E_{signal}(L_f) = E_{Pure}(L_f) \iff \text{Pure Signal}$$

The proposed technique, Section (III-f), is used to monitor the rms-variation during the distortion event and $\Delta E_{Re_f}(L_f)$ is used to monitor the direction of the variation (increased or decreased).

**Fig. (10)** shows the process of classifying and monitoring the rms-variations during any distortion event. Fig. (10a) shows the distorted signal contaminated with the rms-variations that are shown in Table (4). Fig. (10b) shows a different window frame; each frame presents 3 cycles of the distorted signal. The time localization property for different variations is extracted from the detail version of the distorted signal $D_1$ for each frame as shown in Fig. (10c). As the noise level increases, the proposed algorithm in Section (III-c) is used to localize the distortion event. Fig. (10d) shows the variation of distorted signal energy distribution $\Delta E$ with respect to the power frequency resolution level $L_f$. The four lines in Fig. (10d) are:
1. $E_{\text{signal}}(L_f)$ the soiled line on the top.
2. $E_{\text{pure}}(L_f)$ the dotted line on the top.
3. $\Delta E(L_f)$ the dashed line on the top.
4. $\Delta E_{\text{Re}}(L_f)$ the solid line on the bottom.

The first frame in Fig. (10d) shows that the signal $\Delta E(L_f)$ and $\Delta E_{\text{Re}}(L_f)$ are coincident with each other. $\Delta E(L_f)$ is greater than zero which represents a swell phenomenon and $\Delta E_{\text{Re}}(L_f)$ also greater than zero which represents an increase in the rms value. The second frame shows $\Delta E_{\text{Re}}(L_f)$ is less than zero, representing a reduction in the rms of the signal and $\Delta E(L_f)$ is greater than zero, representing a swell phenomenon. The third frame represents a reduction in rms value and sag phenomenon.

The proposed technique is implemented in different sets of simulated data. The results of applying the technique to the distorted signal, shown in Fig. (10a), are presented in Table (5).
Table 5: Non-Rectangular rms-variation measurements

<table>
<thead>
<tr>
<th>Frame #</th>
<th>Actual Variation</th>
<th>Estimated Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mag. (peak)</td>
<td>Time (s)</td>
</tr>
<tr>
<td>1</td>
<td>1.3500</td>
<td>0.0296</td>
</tr>
<tr>
<td>2</td>
<td>0.8775</td>
<td>0.0864</td>
</tr>
<tr>
<td>3</td>
<td>0.1316</td>
<td>0.1391</td>
</tr>
<tr>
<td>4</td>
<td>0.5265</td>
<td>0.1599</td>
</tr>
<tr>
<td>5</td>
<td>0.8424</td>
<td>0.2180</td>
</tr>
<tr>
<td>6</td>
<td>1.0000</td>
<td>0.2702</td>
</tr>
<tr>
<td>7</td>
<td>1.0000</td>
<td>0.3000</td>
</tr>
</tbody>
</table>

V - Conclusion

This paper presents a wavelet-based procedure that will assist in automated detecting, classifying, and measuring of different power system disturbances. The localization property of the wavelet transform is used to detect and measure the distortion duration in a noisy environment. The rms value of the distortion event magnitude is measured using wavelet coefficients. The variations of the rms value during the distortion event are also monitored and measured. The paper conclusion is summarized in the following points:

1. Any distortion in the signal can be detected and localized using wavelet coefficients at the higher resolution level, (16). However, as the noise level increases and the transient event magnitude decreases, the coefficients that represent the noise will merge with those that represent the distortion, the wavelet detection and localization property will no longer be valid at this resolution level.

2. An assessment of the noise level can be determined by computing the energy of the coefficients at the highest resolution level, (17).

3. As the noise levels increase, the distortion event can be localized by reconstructing an approximated version of the distortion event, (18).

4. The energy of the distortion event at different resolution levels is used as a feature vector that can classify different disturbances, (22). These discriminative, translation invariant features with small dimensionality can be used to classify different power quality problems that overlap in time and frequency.

5. The wavelet coefficients of the distortion event can be used to measure the rms value and the THD% of the distorted signal, (28) and (29).

6. A new wavelet-based procedure to characterize rms variations is presented in this paper, Section (III-f). This procedure can help in assessing the quality of service presented in the distribution systems, the quality of the mitigation devices, and the characteristic of the load during rms variation. Utilizing this procedure, a clear picture of any further changes in the harmonic distortion, noise level, or rms variations can be detected, localized, classified, and quantified inside the distortion event.

VI – References


