Multiresolution Signal Decomposition: A New Tool For Fault Detection In Power Transformers During Impulse Tests

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Abstract— **Detection of major faults in power transformers during impulse tests has never been an issue, but is rather difficult when only a minor fault, say a sparkover between adjacent coils or turns, lasting for a few microseconds occurs. However, detection of such type of fault is very important to avoid any catastrophic situation. In this paper, we have proposed a new and powerful method capable of detecting minor incipient faults. The approach is based on wavelet transform analysis, particularly the dyadic-orthonormal wavelet transform. The key idea underlying the approach is to decompose a given faulty neutral current response into other signals which represent a smoothed and detailed version of the original. The decomposition is performed by multiresolution signal decomposition technique. Preliminary simulation work demonstrated here, shows that the proposed method is robust and far superior to other existing methods to resolve such type of faults.**

Keywords— **Power transformer, Impulse-testing, Time-frequency representation, Wavelet transform, Multiresolution signal decomposition**

I. Introduction :

Insulation happens to be the single major cause for most of the failures in power transformers. Due to this reason and in addition to its enormous cost, power transformer utilities resort to the practice of monitoring and diagnostics as possible ways of determining its actual status to enable preventive/corrective measures.

Impulse tests are performed on power transformers to assess its insulation integrity, during which it is subjected to a special sequence of voltages as per standards (IEC 722) [1] and the resulting neutral and or other current oscillograms are recorded. Fault detection using these current records is performed on the basis of the ability to detect the presence of any deviation amongst the records.

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In the earlier days, visual examination of the oscillographic traces were performed and judgement was often controversial, especially when a minor fault had to be resolved. A minor fault can typically be due to a sparkover between adjacent turns or coils, lasting for a few microseconds. Later on, with availability of transient digitizers these records were acquired and stored enabling its post-processing. Initially, post-processing was limited to difference waveforms being amplified and compared. Subsequently, the development of the transfer function approach for fault detection was a milestone [2]. Here, the computed transfer functions at different voltages were compared, and any deviations, if observed, were attributed to be due to a fault in the transformer. However, contrary to the main philosophy of this approach, practical testing has indicated many serious problems with regard to it being independent of the input excitation and chopping times [3]. The possible sources leading to errors and ambiguity in the transfer function computation could be due to one or more of the following reasons

- Noise inherent in acquired data
- Errors due to sampling, quantization, A/D errors, finite record length effects
- Different signal processing methods being adopted like, windowing, filtering etc.

It is perhaps due to these reasons, this approach has not yet found its way into relevant standards. Given the subtle nature of the problem and huge costs involved, it becomes imperative that newer and powerful methods capable of detecting minor incipient faults have to be continually explored.

Recently, the second author proposed a new method for detecting minor faults, based on the principle of *joint time-frequency* analysis using short-time Fourier and wavelet transforms [4]. Here, the neutral current was analyzed directly and treated as a non-stationary signal whose properties change or evolve with time, when there is a fault. This is particularly true, when a momentary short-circuit occurs between adjacent turns/coils due to high stress levels. This change manifests as a short duration, low magnitude, fast decaying transient superposed on the main neutral current. The proposed method was shown to be capable of clearly resolving even such minute variations, which the transfer function approach was unable to do. An additional advantage was that only the neutral current record was required. Continuing on the same lines, the authors here propose another related tool, namely *Multiresolution Signal Decomposition* for detecting such kind of faults. This tool is far superior when compared to the earlier one, in terms of computational efficiency and detection capabilities.

After a detailed comparison of the new approach with the earlier ones in Section II, a brief theoretical description of multiresolution signal decomposition is given in Section III. Section IV deals with data generation followed by the choice of the mother wavelet in section V. Simulation results are discussed in Section VI followed by conclusions.

II. Advantages Over the Earlier Approach :

Wavelet analysis is a rapidly evolving tool with growing applications in science and engineering. The wavelet transform (WT) indicates the degree of similarity between the signal and a *basis function*, called *mother wavelet* and is achieved by dilating the *mother wavelet* and translating it over the signal. Thus, WT maps one dimensional time-domain signal to a two dimensional function of time and scale (scale relates to frequency). Due to this, the *time-scale* diagram is called a *scalogram* instead of a *spectrogram*. This three dimensional plot gives an indication as to which frequency components are present at what times. Thus, it yields a potentially more revealing pictorial representation enabling a signal processor to analyze temporal localization of the spectral components of the input signal.

Any sudden change in the signal record (resulting due to a fault) can be clearly identified as a local protrusion or change in magnitude on the *scalogram* plot. Applicability of these *time-frequency* tools for detecting presence of short duration, low amplitude transients superposed on the neutral current has been recently reported [4]. This was found to have far superior detecting abilities compared to the transfer function method. However, the following disadvantages were encountered

- Some expertise is required in studying the *scalogram* or *spectrogram* plots to detect faults
- Instead of time domain, this involves close examination of signal information on the *time-frequency* plane
- Since the transformation is achieved by dilating and translating the *mother wavelet* by very small steps, generation of *scalogram* is computationally not efficient and consumes lot of time. Additionally, it yields substantial redundant information as well.
- Many a times signal reconstruction becomes unstable i.e. perfect reconstruction of signal is not possible

To overcome most of these problems, the proposed method utilizes a *dyadic-orthonormal wavelet* transform analysis to detect and accurately localize occurrence of minor faults in the neutral current records. The key idea underlying this approach is that *dyadic-orthonormal wavelet* transform decomposes the signal into two other signals, which represent a smooth and detailed version of the original signal. This operation is termed as *multiresolution signal decomposition* (MSD). There exist several advantages of MSD technique over the method introduced in [4]. They are as follows

- The MSD technique involves the close examination of only two or three detailed and one smoothed signal component in time domain.
- It is very easy to detect the presence of sudden changes in the signal from the decomposed signals.
- Since signal representation is done using an *orthonormal basis* function, information redundancy among the decomposed signals does not exist.
- There exists an elegant algorithm (*pyramidal algorithm*) to implement MSD technique. This makes the technique computationally very efficient.
- Perfect reconstruction of the signal from the decomposed components is guaranteed.

III. Multiresolution Signal Decomposition :

Over the past few years, MSD technique has been successfully applied to extract relevant information of signals in many fields. *Multiresolution signal decomposition* was formulated based on the study of orthonormal, compactly supported wavelet bases. It decomposes a signal $x(t)$ of $L^2(R)$ into its detailed and smoothed versions. The MSD concept, initiated by Meyer [5] and Mallat [6], provides a natural framework for the understanding of wavelet bases. Here, we give a brief description of orthonormal, compactly supported wavelet bases; which has been discussed in detail in [7] and [8].

An orthonormal compactly supported wavelet basis of $L^2(R)$ is formed by the dilation and translation of a single function $\psi(t)$, called the *mother wavelet* function and is given by

$$\psi_{j,k}(t) = 2^{-j/2} \cdot \psi\left(\frac{t-2^j k}{2^j}\right);\; j,k \in Z, \qquad (1)$$

where Z is the set of integers. In equation (1), the function ψ has M vanishing moments up to order $M-1$ and it satisfies the following *two-scale difference equation*,

$$\psi(t) = \sqrt{2}\sum_{k=0}^{L-1} g_k \phi(2t-k) \qquad (2)$$

where $\phi(t)$ is a companion function of the wavelet function, which is also called *scaling function* and forms a set of orthonormal bases of $L^2(R)$ as given below.

$$\phi_{j,k}(t) = 2^{-j/2} \cdot \phi\left(\frac{t-2^j k}{2^j}\right);\; j,k \in Z, \qquad (3)$$

The *scaling function* $\phi(t)$ satisfies,

$$\int_{-\infty}^{+\infty} \phi(t)\cdot dt = 1 \qquad (4)$$

and *two-scale difference equation*,

$$\phi(t) = \sqrt{2}\sum_{k=0}^{L-1} h_k \phi(2t-k) \qquad (5)$$

In equation (2) and (5), two coefficient sets $\{g_k\}$ and $\{h_k\}$ have the same finite length L for a certain basis, where L is related to the number of vanishing moments M in $\psi(t)$. For example, L equals $2M$ in the *Daubechies' wavelets.* In the wavelet representation of signals, $\{h_k\}_{k=0,1,\ldots,L-1}$ behaves as a low-pass filter and $\{g_k\}_{k=0,1,\ldots,L-1}$ behaves as a high-pass filter to the input signals. These two filters are related by

$$g_k = (-1)^k \cdot h_{L-k}; \quad k = 0, \ldots, L-1, \tag{6}$$

and are called *quadrature mirror filters* (QMF). An extensive study of the QMF can be found in [9].

To illustrate the concept of multiresolution decomposition for one dimensional signal, let us consider Fig. 1 as shown below. Here, V_j represents the set of orthonormal, translated scaling functions at a fixed dilation of the *scaling function* $\phi_{j,k}(t)$ and W_j represents the set of compactly supported orthonormal, translated wavelet functions at a fixed dilation of the *mother wavelet* function $\psi_{j,k}(t)$. Furthermore, W_j is orthogonal complement of V_j in V_{j-1}, they are related by

$$V_{j-1} = V_j \oplus W_j \tag{7}$$

Figure 1 illustrates the nesting of subspaces V_j and their orthogonal complements W_j. In addition, V_0 contains the original data which has the finest resolution. The projection of the data on $\{V_j; j = 1, 2, 3 \ldots\}$ has increasingly coarser resolution. In this paper, the data projected onto the V_j is referred as the decomposition of the data at resolution level j.

We define the projection of a function $f(t) \in V_0$ to be $f^j(t)$. Then the J^{th} resolution level of the function has the form

$$f^j(t) = \sum_k S_{j,k} \cdot \phi_{j,k}(t) \tag{8}$$

where $S_{j,k}$ is the projection of the function $f(t)$ on the basis $\phi_{j,k}(t)$; that is,

$$S_{j,k} = \int f(t) \cdot \phi_{j,k}(t)\, dt \tag{9}$$

Next, define the projection of $f(t)$ on the subspace $\psi_{j,k}(t)$ to be

$$df^j(t) = \sum_k d_{j,k} \cdot \psi_{j,k}(t) \tag{10}$$

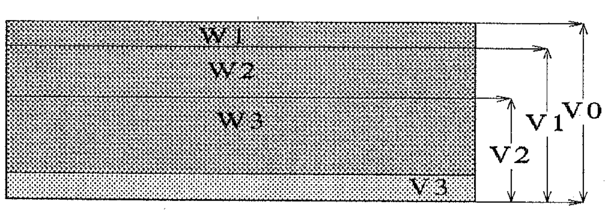

Fig. 1. Illustration of the sequence of the multiresolution analysis subspaces V_j. W_j is the orthogonal complement of V_j in V_{j-1}. Space V_0 represents the space that contains the finest resolution data.

where $d_{j,k}$ is the projection of function $f(t)$ on the basis $\psi_{j,k}(t)$

$$d_{j,k} = \int f(t) \cdot \psi_{j,k}(t)\, dt \tag{11}$$

Then it can be derived that the original function $f(t) \in V_0$ can be represented by

$$f(t) = f^{n_0}(t) + \sum_{j=n_0}^{1} df^j(t) \tag{12}$$

or

$$f(t) = \sum_k S_{n_0,k} \cdot \phi_{n_0,k}(t) + \sum_{j=n_0}^{1} \sum_k d_{j,k} \cdot \psi_{j,k}(t) \tag{13}$$

IV. Implementation of MSD :

In general, the MSD term holds in all the procedures to obtain low-pass approximations and band-pass detailed signals from any original input signal or image.

An approximation or smoothed signal is a low resolution representation of the original signal while a detailed signal is the difference between two successive low resolution representations. These approximations and detailed signals are obtained through filter bank structures similar to the wavelet transform schemes, using the analysis filters h_k (low pass) and g_k (high pass) as mentioned above and the synthesis filters hr_k (low pass) and gr_k (high pass). To generate *Daubechies' orthonormal wavelet*, hr_k and gr_k are derived from the h_k and g_k and have the following relation;

$$hr_k = h_{L-k}, \quad k = 0, \ldots L-1,$$

$$gr_k = g_{L-k}, \quad k = 0, \ldots L-1,$$

So, the MSD implementation is a multiresolution analysis-synthesis tree, based on wavelet transform. The analysis-synthesis tree is shown in Fig.3 for the case $j = 2$.

For more scales, the tree must be continued downwards the dashed arrow. The outputs after the synthesis stage are the detailed signals $d_x^j\, j = 1, \ldots, j$ and the approximation signal a_x^j. In other words, the MSD algorithm performs the following two main operations

- The analysis filter bank divides the spectrum into octave bands.
- The synthesis filter performs an independent inverse transform operation for each of the generated subbands.

That is, each of the wavelet transform subbands is reconstructed separately from each other. Finally, summing all the detailed and approximation components, one can obtain the original signal.

V. Data Generation and Simulation :

In this work, neutral current responses due to a standard lightning impulse voltage and a sharp chopped impulse voltage are used. As insulation stresses experienced by transformers due to these waveshapes is extreme, so failure detection under these two conditions will definitely be a good index of the applicability of any method.

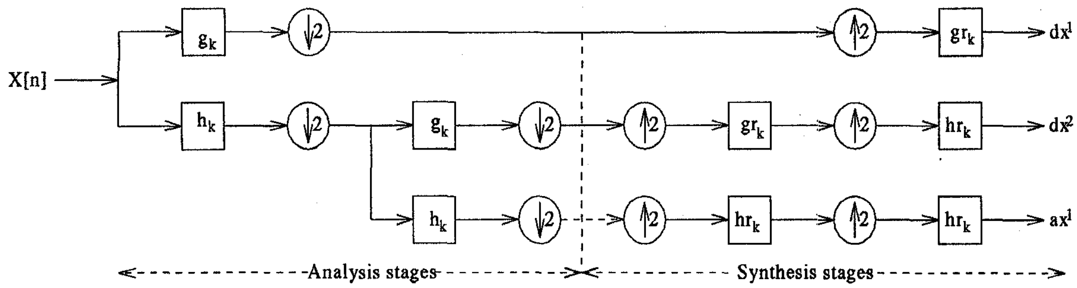

Fig. 2. Analysis-synthesis tree for MSD

The approach described by GURURAJ [10] enables calculation of neutral current waveforms for any input excitation for a typical power transformer model. Also, it has been well established that initial effects of the faults manifest themselves in the neutral current with a delay of about $1 - 2\,\mu s$ after the peak is reached in the case of standard lightning impulse voltage, and chopping instant in case of chopped impulse voltage. This situation is simulated by superimposing a short duration, low amplitude, fast decaying and oscillating signal onto the neutral current, starting at time instant $t = 8\,\mu s$ for the chopped wave response and time instant $t = 3\,\mu s$ for the standard lightning response.

Mathematically it is modelled as

$$I_f = I_m \sin(2\pi f t)\, e^{-\tau t}$$

Its frequency (f), and decay time-constant (τ), are chosen as $1.5\,MHz$ and $.2\,\mu s$ respectively. The actual peak of the superposed transient signal was 7.5% of the neutral current peak in each case. The goal is to detect as small a change as possible under these circumstances.

VI. Choice of mother wavelet :

The choice of *mother wavelet* plays a significant role in detecting and localizing different kinds of signal changes. In addition to this, the choice also depends on the nature and kind of the signal which has to be detected. In the present case, we are interested in detecting low amplitude, short duration, fast decaying and oscillating type of signals. One of the most popular orthonormal wavelet is *Daubechies' wavelet* which has been shown to possess abilities for such kinds of detection problems [5]. A MATLAB compatible code (available at http://www.tsc.uvigo.es/~wavelets) has been used to generate this wavelet.

Daubechies' wavelet with various filter coefficient were studied and it has been found that larger filter coefficients generate more localized wavelets in both time and frequency dimension. In order to clearly illustrate, the effect compact support has on the detecting abilities, two *Daubechies' wavelets,* one with 8 filter coefficients and another highly localized with 56 filter coefficients were chosen, and are shown in Fig.3. Capability of these two mother wavelets in detecting the faults will be discussed in next section.

The wavelet analysis is a measure of similarity between the basis functions (wavelets) and the signal itself. Here the similarity is in the sense of having similar frequency content. So, in this case the mother wavelets must be highly localized in time and frequency as well in order to have good detecting properties.

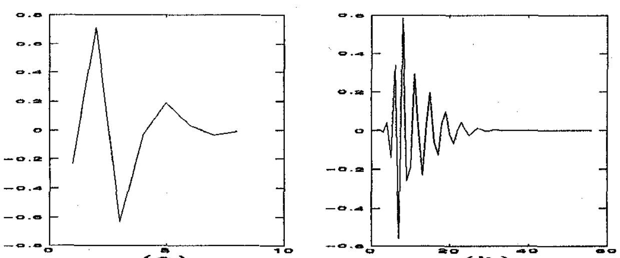

Fig. 3. *Daubechies' wavelets* with (a) 8 filter coefficients and (b) 56 filter coefficients.

VII. Result and Discussion :

From the neutral current responses due to the full and chopped wave, two more records are generated by the superposition of the fault component at specific time instants as already described. Before analyzing the capability of the MSD method, we first evaluate the performance of other fault detection methods.

First, the neutral currents for both cases , with and without superimposed fault are shown in Fig. 4. Since, the superimposed fault component is a low magnitude decaying transient, and lasts for a few microseconds only, it is very difficult to visually detect changes in the faulted neutral current. Also, in practice due to presence of noise, it will be difficult to detect such minor short duration faults by directly inspecting the difference between neutral currents records.

Secondly, the detecting ability of the transfer function approach to such superimposed fault is investigated . Transfer function (defined as the ratio of Fourier transform of the neutral current to the Fourier transform of the input excitation) computed with and without fault are shown in Fig. 5 for both cases. It can be seen, that due to the inclusion of the fault, there are small variations in the transfer function. However, its effect is global i.e. spread throughout the spectrum, due to which neither the frequency content of the fault can be determined, nor can the time of its occurrence. However, this method is able to resolve the superimposed transient signals only when its magnitude is

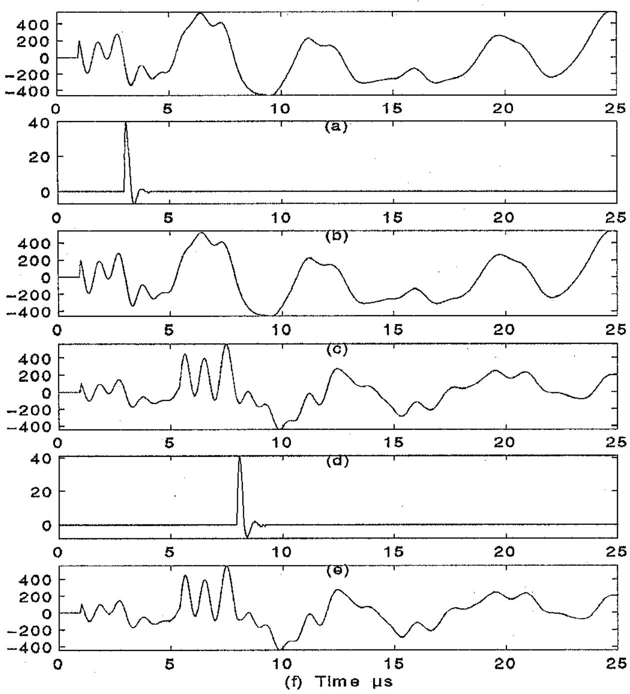

Fig. 4. Effect of superimposing faults on neutral currents: (a) Standard lightning impulse wave, no fault. (b) Superimposed fault at $t = 3\mu s$ (c) Standard lightning impulse wave, with fault. (d) Chopped impulse wave, no fault. (e) Superimposed fault at $t = 8\mu s$ (f) Chopped impulse wave, with fault.

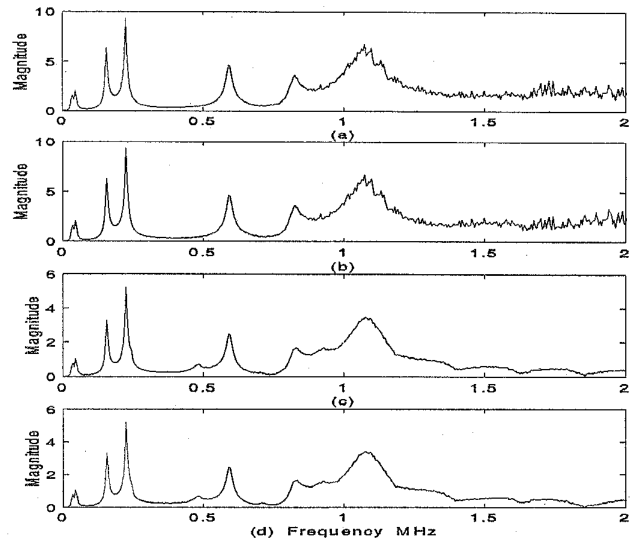

Fig. 5. Effect of superimposing faults on transfer function: (a) Standard lightning impulse wave, no fault. (b) Standard lightning impulse wave, with fault (c) Chopped impulse wave, no fault. (d) Chopped impulse wave, with fault.

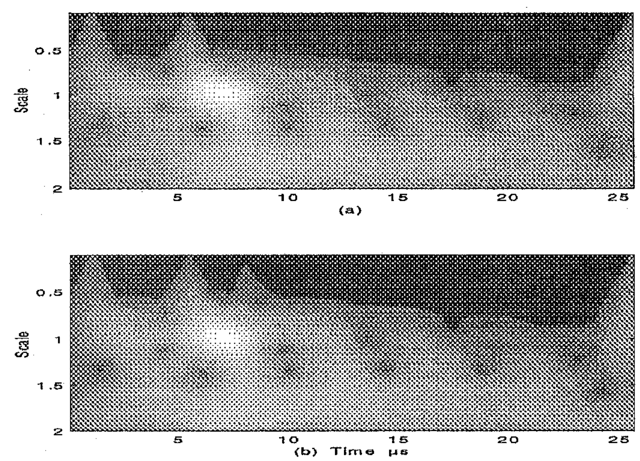

Fig. 6. Effect of superimposing faults on scalogram for the chopped impulse wave. (a) no fault. (b) with fault.

appreciably high.

The ability of the scalogram approach to detect fault is illustrated next. Using a morlet wavelet ($e^{jat} \cdot e^{-\frac{t^2}{2\sigma}}$, where a and σ are modulating and scaling parameters) as the basis function, scalogram for the neutral current (without and with fault) the case of chopped wave is shown in Fig. 6. The two local finger-like projections at the instants of beginning and chopping of the wave, reveal the high frequency contents at those particular time instants. The appearance of any such additional projection will indicate the presence of a sudden change in the signal. In Fig. 6 b, an additional structure is appearing at exactly the same time instant where the transient signal is superimposed onto the neutral current. Thus, the exact time at which the fault has occurred and also the frequency component of the fault can be extracted from the scalogram. Though this method has good detecting ability, yet there are certain operational difficulties which have been highlighted in Section II.

Finally the ability of the proposed MSD technique is investigated. Here, the primary objective is to resolve the presence of fault by inspecting the detailed component time domain signals. For this purpose, two or three scale signal decomposition was found enough to discriminate the transient signal from the original. In this simulation study, *Daubechies' dyadic filter* function (i.e. each dilation of h_k effectively halves the bandwidth of $H(e^{j\omega})$) is used to decompose the neutral current response, which has been sampled at $20MHz$. Thus, a three scale decomposition of a signal yields three detailed signals having a frequency band of $10-5MHz$ at scale 1, $5-2.5MHz$ at scale 2 and at scale 3, $2.5-1.25MHz$ and one smooth signal contains frequency band $1.25MHz$ to DC level.

First, the neutral current response due to the chopped impulse voltage (without fault) is decomposed using *Daubechies' filter* function with $L = 56$, and the corresponding plots are shown in Fig. 7. The detailed signals have two sharp spikes, one at the beginning of wave and second at the instant of chopping, illustrating the high frequency components present in the neutral current at those time instants. These are seen in all the three bands.

Figure 8 & 9 show the three scale decomposed signal of neutral current response having superimposed transient signal for the case of chopped impulse wave with *Daubechies' filter* function with $L = 8$ and $L = 56$ respec-

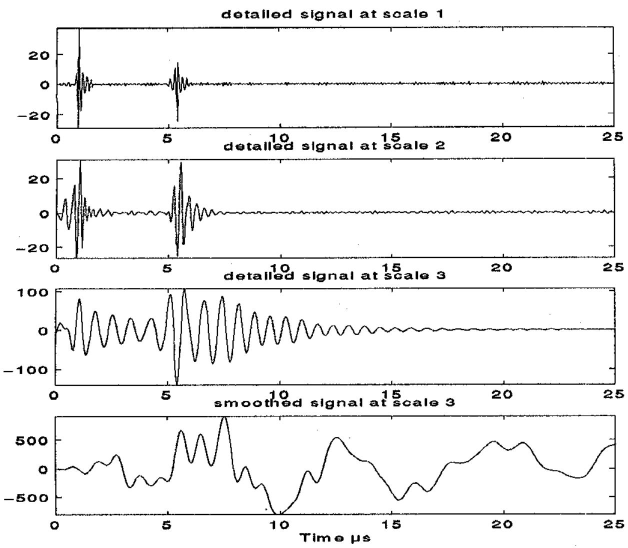

Fig. 7. 3 *scale* decomposed signals using $L = 56$ for chopped impulse wave, no fault

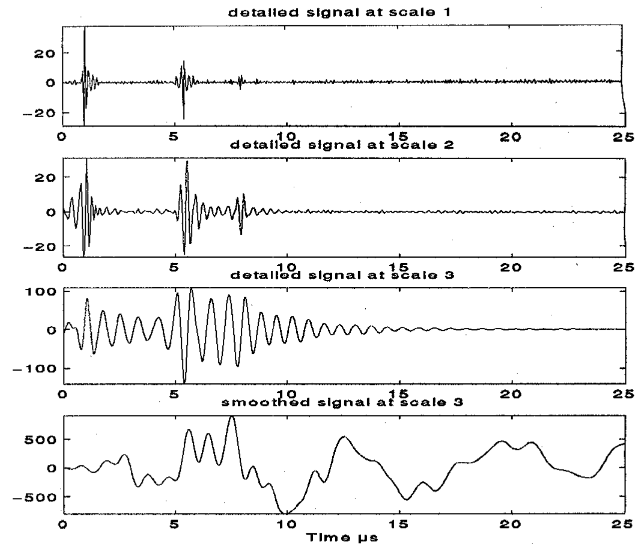

Fig. 9. 3 *scale* decomposed signals using $L = 56$ for chopped impulse wave, with fault

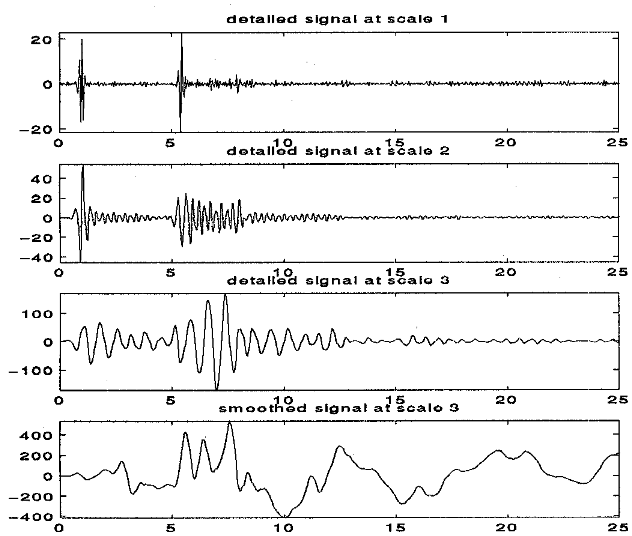

Fig. 8. 3 *scale* decomposed signals using $L = 8$ for chopped impulse wave, with fault

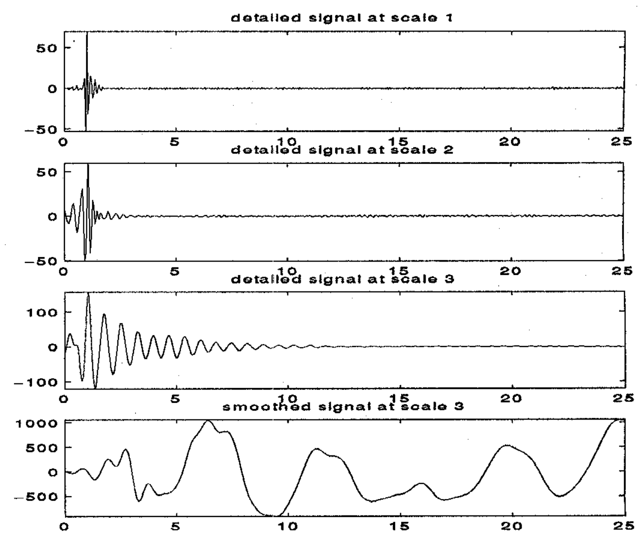

Fig. 10. 3 *scale* decomposed signals using $L = 56$ for standard lightning impulse wave, no fault

tively. The appearance of a new transient signal in addition to the two at the beginning of the signal and chopping time instant indicate the presence of a fault. The time of occurrence of the new spike, in Figs. 8 & 9 exactly coincide with the time at which the fault has been superposed. Thus, the time at which a fault has occurred can be accurately estimated.

Each detailed signal represents a band of frequencies. The superimposed fault (exponentially damped sinusoidal), which has a fundamental frequency of $1.5MHz$ contains a number of neighbouring frequency components due to leakage. Due to this fact, when MSD technique is applied, the neighbouring bands show the presence these frequency components, see Fig. 8 & 9. With $L = 8$ there is poor localization of fault as depicted in Fig. 8. Therefore, it become necessary to use more localized wavelet for better localization of fault. Figure 9 shows the good localization of fault when $L = 56$ was used. Thus MSD technique enables detection and localization(exactly in time domain) of such type of faults. Secondly, the simulation results for standard lightning impulse wave, in the absence and presence of the fault are shown in Fig. 10 and Fig. 11 respectively. The abrupt change that occurs at the beginning of the lightning impulse wave is reflected as high frequency components in the neutral current at the corresponding time instant. This is depicted in Fig. 10 & Fig. 11. Therefore, the presence of the first short duration transient signal in the detailed signal component is inherent. The second

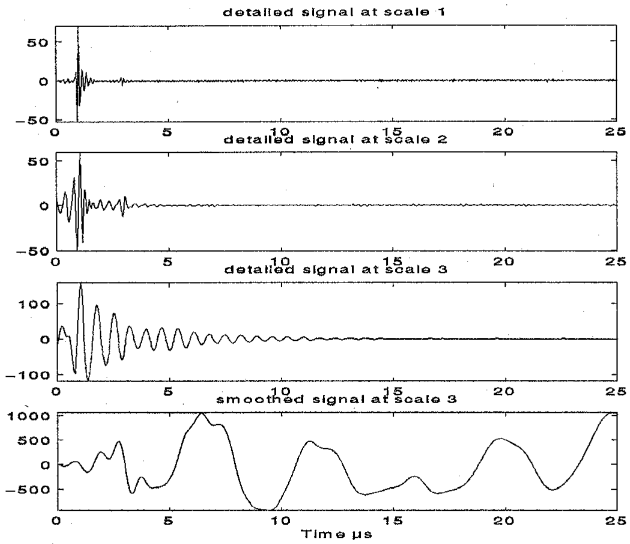

Fig. 11. 3 *scale* decomposed signals using $L = 56$ for standard lightning impulse wave, with fault

spike is an indication of a fault and is illustrated in Fig. 11.

To make the simulation realistic, an initial delay of 1 μs, analogous to the pre-trigger delay in acquired waveform was purposely introduced into all the data sets. To all these signals white gaussian noise(peak to peak amplitude was around 1.0% of the peak amplitude of neutral current) was added. Finally, assuming a 10 bit digitizer these data sets were quantized.

Thus, the ability of the MSD method to detect and localized the presence of minor faults present in neutral current signal records, for both chopped and full wave has been clearly demonstrated. From the simulation studies it is evident that this tool has the potential to address such tasks.

VIII. Conclusion :

A new technique has been proposed for fault diagnosis in *Power transformers* based on *multiresolution signal decomposition* of neutral currents. This is found to have many advantages over the existing methods. The preliminary simulation results reported here, shows that the proposed method is robust and far superior to other existing methods to resolve such type of faults.

Some practical aspects has been considered in this simulation study but more tests will have to be done to gauge its suitability *under real-world* conditions. In addition, as discussed in this paper, the choice of the *mother wavelet* function used to decompose the signal is critical for this application. More facts about sensitivity of basis function for MSD technique remains to be investigated.

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