APPLICATION OF CONTINUOUS & DISCRETE WAVELET TRANSFORM FOR STUDYING OF VOLTAGE FLICKER-GENERATED SIGNAL

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ABSTRACT

Flicker evaluation considering power system disturbances becomes a challenging task. This paper introduces voltage fluctuation and flicker analysis by using wavelet transform. A method of applying continuous wavelet transform (CWT) against discrete wavelet transform (DWT) for the study of voltage flicker-generated signals is proposed. The analysis accuracy of voltage flicker-generated signal is dependent on the high degree of frequency resolution. An evaluation of different Wavelet basis functions for investigating the voltage flickers was applied. The results obtained can be the basis for a flicker monitoring system based on Wavelet Transform that in future it may be produced and handled in the market. Signal components at any frequency of interest can easily be supervised and the most characteristic wavelet function tagged. The simulation work is done by using Matlab. The results are recorded accompanied by many analysis and comments.

INTRODUCTION

Flicker differs from other power distortions because it deals with the effect of the power quality on humans rather than on equipment. Since most buildings use electrical lighting, power fluctuations cause lighting fluctuations. The result of this can be simply annoying, producing headaches and eye fatigue. The IEC standards define flicker in standards IEC 868 [1]. Studies demonstrated that the response of the human eye has the characteristic of a band-pass filter between 0.5 Hz and 35 Hz, with maximum sensitivity to the luminous flux at a frequency around 8 Hz to 9 Hz. The voltage fluctuation necessary to produce perceptible flicker is independent of the type of supply voltage (AC or DC) used for the lamp. So, the light flicker effect is one of the most complex phenomena in the power quality field. It involves voltage fluctuation shape, lamp behavior, and eye–brain activity.
Voltage fluctuation, or flicker, degrades the operation performance of motors and generators, reduces the life of electronic devices, and influences visual perception of lights. As the electric power quality has become an important issue, the study of voltage flickers is critically important from both public comfort and operational reliability perspectives. So, to study and analyze the flicker effect, it is required to use modern technique for signal processing. The wavelet theory can be seen as the emerging technology in the research of signal processing. In contrast to those Fourier transform-based approaches where a window is used uniformly for spread frequencies, the wavelet uses short windows at high frequencies and long windows at low frequencies [2].

As a first step for flicker analysis, different types of continuous wavelet transform (CWT) like Haar, Daubechies (dbN), Morlet& Mexican Hat are tested to find the suitable ones to extract coefficients. For Daubechies, it is established that N is the order and db is the surname. By plotting these coefficients, the portion of the flicker can be diagnosed through the power signal. At the second step for flicker analysis, discrete wavelet transform (DWT) with the suitable ones decided in the first step, can decompose the signal into several energy levels. These Wavelet decompositions would be utilized to construct a proper feature vector to train an intelligent classifier for an efficient detection of voltage flickers [3] & [4].
In this paper, the complete analysis of the first step will be produced. Also, good overture for the ongoing research for the second step is offered. Under Matlab - Wavelet Toolbox, the results are verified with many demonstrations.

VOLTAGE FLICKER MODELING

Flicker levels are characterized by two parameters [5]:
- Short-term flicker (P_{st}): a value measured over 10 minutes that characterizes the likelihood that the voltage fluctuations would result in perceptible light flicker.
- Long-term flicker (P_{lt}): a value derived from 2 hours of P_{st} values (12 values combined in cubic relationship).

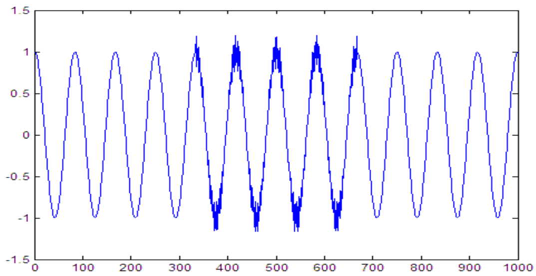


Fig. (1): Normal sinusoidal signal combined with generated flicker signal.

However, in a short period, the voltage flicker can be appropriately modeled as an amplitude-modulated waveform, where the modulating signal is a sinusoid of random frequency and random magnitude. A voltage signal containing flicker can be thus expressed as:

$$f(t) = \cos(t) + (0.2\cos(10\pi t)(\cos(t))) \quad (1)$$

A normal sinusoidal voltage signal combined with generated voltage flicker giving the shape in Fig. (1). The flicker period can be noticed at sampling value from 350 to 650.

WAVELET TRANSFORM

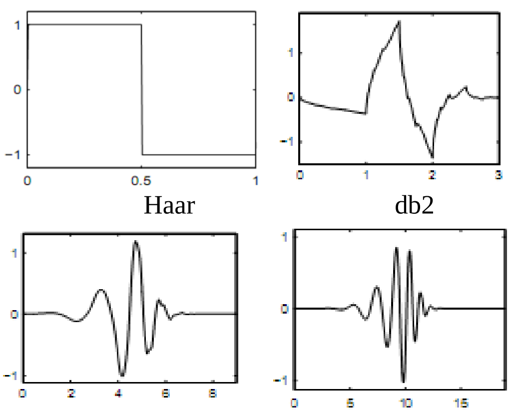
Wavelets are functions that satisfy certain requirements. The name wavelet comes from the requirement that they should integrate to zero, 'waving' above and below the x-axis. The diminutive connotation of wavelet suggests the function has to be well localized. Given a function *f(t)*, its continuous wavelet transform (CWT) will be calculated as follows [6]:

$$WT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \Psi^{*}\left(\frac{t-b}{a}\right) dt \qquad (2)$$

Where, a and b are the scaling (dilation) and translation (time shift) constants, respectively. The term $\Psi(t)$ is the wavelet function 'mother wavelet' and its dilation and translation are simply 'wavelets'. Wavelet transform of sampled waveforms can be obtained by implementing the discrete wavelet transform, which is given by:

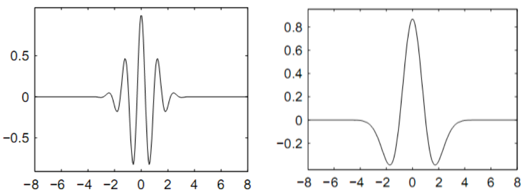
$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_{k} f(k) \Psi^{*}\left(\frac{n - k a_0^m}{a_0^m}\right) dt \qquad (3)$$

Where, the parameters a and b in Eq. (2) are replaced by a_0^m and $k a_0^m$, k and m being integer variables. In a standard discrete wavelet transform, the coefficients are sampled from the continuous WT on a dyadic grid, a_o = 2 and $b_o = 1$, yielding $a_0^0 = 1$, $a_0^{-1} = 1/2$, etc. $b = k \times 2^{-i}$, i being an integer variable. Actual implementation of the discrete wavelet transform, involves successive pairs of high-pass and low-pass filters at each scaling stage of the wavelet transform. This can be thought of as successive approximations of the same function, each approximation providing the incremental information related to a particular scale (frequency range), the first scale covering a broad frequency range at the high frequency end of the spectrum and the higher scales covering the lower end of the frequency spectrum however with progressively shorter bandwidths. Conversely, the first scale will have the highest time resolution and higher scales will cover increasingly longer time intervals. There are many kinds of wavelets. One can choose between smooth wavelets, compactly supported wavelets, wavelets with simple mathematical expressions, wavelets with simple associated filters, etc. Fig. (2) shows some types of wavelets [7].



Haar db2

db5 db10



Morlet Mexican Hat

Fig. (2): Some types of wavelets

FLICKER ANALYSIS WITH CWT

It is required to operate the signal analysis using (CWT) using different types of wavelets to find the suitable ones to extract coefficients. Fig. (3) illustrates a plot of the coefficients of Haar wavelet. Also, it includes the coefficient line plot corresponding to a certain scale 'a', and the local maxima plot, which displays across scales (from 64 down to a=1) of the coefficient local maxima for the Harr Wavelet which is the first order of Daubechies (db1).

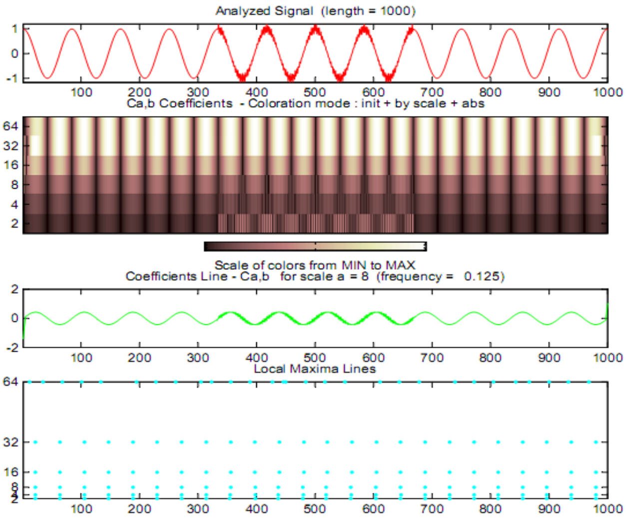


Fig. (3): Flicker signal analysis using Harr Wavelet

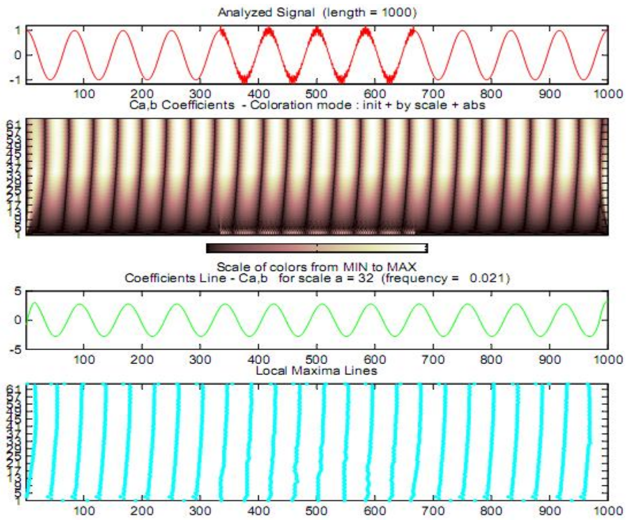


Fig. (4): Flicker signal analysis using db2 Wavelet

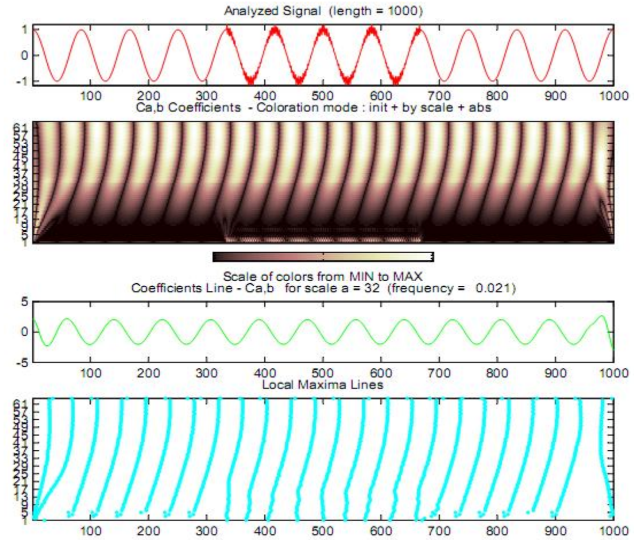


Fig. (5): Flicker signal analysis using db5 Wavelet

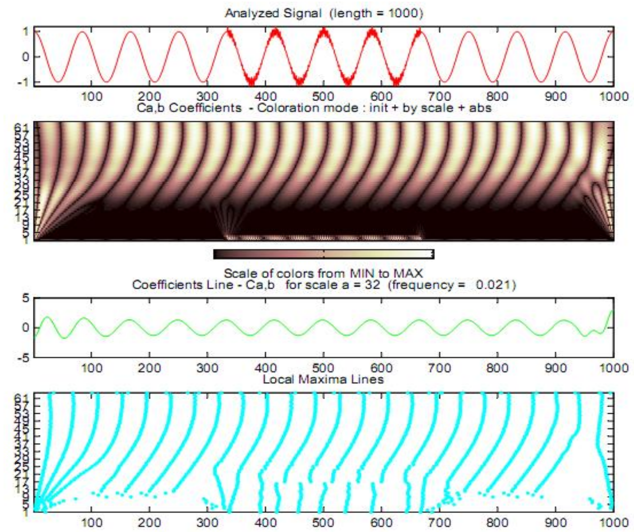


Fig. (6): Flicker signal analysis using db10 Wavelet

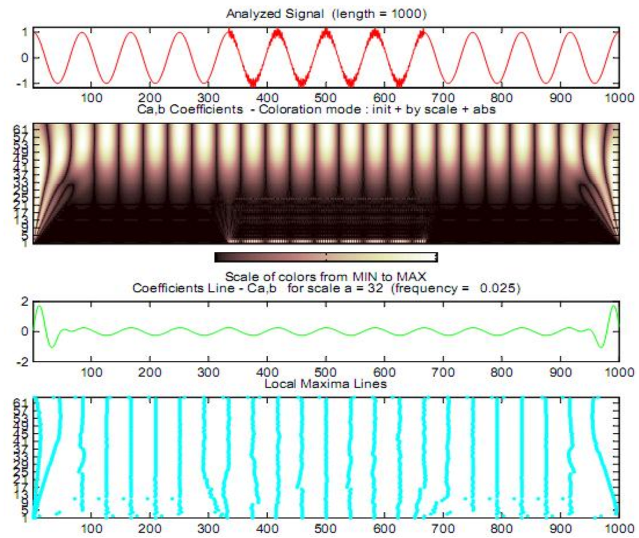


Fig. (7): Flicker signal analysis using Morlet Wavelet

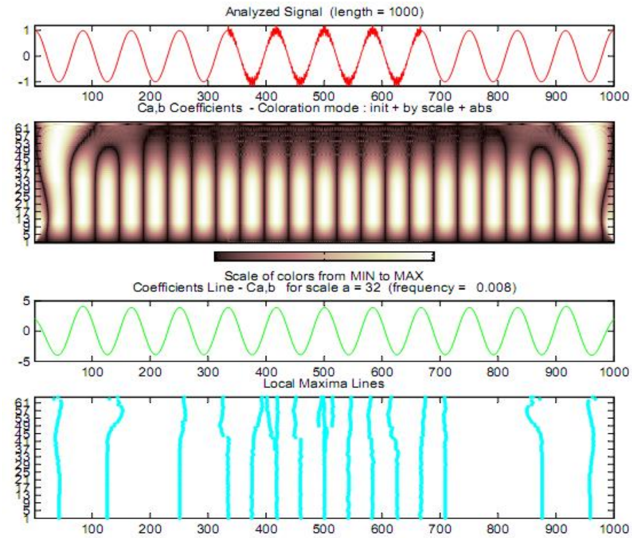


Fig. (8): Flicker signal analysis using Mexican Hat Wavelet

Figs. from (4) to (8) demonstrate the same plots as illustrated in Fig. (3), but for db2, db5, db10, Morlet & Mexican Hat Wavelets, respectively. From the coefficients plots, it is found that Harr is the clearer Wavelet for recognizing the period of the flicker along the proposed signal. Also, Morlet can identify the flicker period clearly. The db1, db5, db10 can identify the flicker period less clearly. On the other hand, Mexican Hat Wavelet cannot recognize the flicker period at all. It is noticed that the flicker period can be distinguished clearly by the types of wavelets that have nearly symmetrical shapes at the vertical or horsetail axes. So, it is recommended to use Haar or Morlet Wavelets to detect flicker period.

DISTINGUISHING BETWEEN CWT AND DWT

It is well known that, any signal processing performed on a computer using real - world data must be performed on a discrete signal [7]. But unlike the discrete wavelet transform, CWT can operate at every scale, from that of the original signal up to some maximum scale that can be determined by trading off the need for detailed analysis with available computational horsepower. The CWT is also continuous in terms of shifting: during computation, the analyzing wavelet is shifted smoothly over the full domain analyzed function.

But, in fact, calculating wavelet coefficient at every possible scale is a fair amount of work, and it generates an awful lot of data. So, it is required to choose only a subset of scales and positions at which to make the calculations. It turns out, rather remarkably, that if the user chooses scales and positions based on powers of two, so called, dyadic scales and positions, then the analysis will be much more efficient and just as accurate. Such an analysis can be obtained from the discrete wavelet transform (DWT). An efficient way to implement this scheme using filters was developed in 1988 by

Mallat [8]. The Mallat algorithm is in fact a classical scheme known in the signal processing community as a two-channel sub band code. This very practical filtering algorithm yields a fast wavelet transform - a box into which a signal passes, and out of which wavelet coefficients quickly emerge. For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. In wavelet analysis, it is often spoken of approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. The filtering process, at its most basic level, can be shown in Fig. (9).

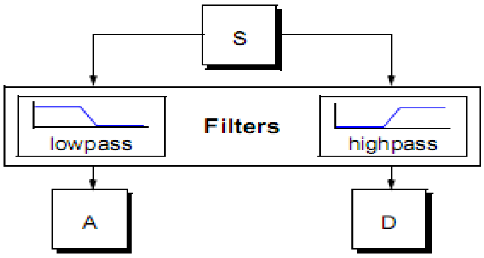


Fig. (9): DWT basic analysis

The original signal, S, passes through two complementary filters and emerges as two signals: "A" which is called approximation and "D" which is called details. These signals "A" and "D" are interesting as there exists a more subtle way to perform the decomposition using discrete wavelets.
This decomposition of the signal into several levels according to various types of Wavelet functions, that chosen previously from the Flicker analysis with CWT, is undertaken. Signal components at any frequency of interest can also be easily supervised and the most characteristic wavelet function tagged. Finally, it possibly will be concluded that Discrete Wavelet decompositions can be utilized to construct a proper feature vector to train an intelligent classifier for an efficient detection of voltage flickers.

CONCLUSIONS

From the previous donation along the paper, it can be concluded that:
- CWT analysis is used as a first step for flicker analysis, to examine different types of wavelets like Haar, Daubechies, Morlet& Mexican Hat to find the suitable ones to extract coefficients.
- From the coefficients plots, it is found that Harr & Morlet can recognize the flicker period clearly.
- The db1, db5, db10 can identify the flicker period less clearly.
- Mexican Hat Wavelet cannot recognize the flicker period at all.
- The flicker period can be distinguished clearly by the types of wavelets that have almost symmetrical shapes at the vertical or horsetail axes.
- Continues wavelet transform (CWT) is not recommended to be utilized to construct a vector to train an intelligent classifier for detecting of voltage flickers as calculating wavelet coefficient at every possible scale is a fair amount of work, and it generates an awful lot of data that will be hard to train any type of intelligent classifier like neural networks or fuzzy logic.
- To implement an intelligent classifier for detecting of voltage flickers, it is recommended to use the discrete wavelet (DWT) decompositions with Harr & Morlet.

FUTURE WORK

According to the concluded results presented in this paper, it is intended to report an ongoing research where Discrete Wavelet decompositions would be utilized to construct a proper feature vector to train an intelligent classifier for an efficient detection of voltage flickers. The outcomes obtained can be the basis for a flicker monitoring system based on Wavelet Transform that, in future, it may be produced and handled in the market.

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