Performance Analysis Of Singularity And Irregular Detection In Human Health Monitoring Using Lipschitz Exponent Function

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Abstract – In this paper, we have presented a novel method for measuring Lipschitz exponent and his Paper was proposed using wavelets, based on the slope of the line, it minimizes the objective function. Singularity and dynamical behavior are two important aspects in signal processing that carries most of signal information. A property of the wavelet transform is its ability to characterize the local regularity of functions. In mathematics, this local regularity is often measured with Lipschitz exponents (LE). The singularity, by means of a Lipschitz exponent of a function, is measured by a graph using slope of a log-log plot of scales and wavelet coefficients along modulus maxima lines of a wavelet transform. The results of experiment demonstrate that this method is more precise and robust. Most of the singularity measures have a performance similar to that of ISWM and considerably better than that of WTMM. These findings add weight to the view that wavelet analysis methods offer an effective way forward in the quantitative analysis of human EEG signal to assist the clinician in the diagnosis of brain disorders. The Lipschitz Exponent (LE) is the most popular measure of the singularity behavior and the irregular structure of a signal.

Key words: Singularity, Wavelet Transform Modulus Maxima, Lipschitz Exponent.

I. INTRODUCTION

Singularities and irregular structures often carry the most important information from the bio signals. Because singularity often carries the most important information contained in a bio signal, singularity analysis has emerged as a multiple area problem solving method in recent years. In mathematics, the singularity is usually measured with Lipschitz exponent. It is a real number that can characterize the local regularity or smoothness in the signal. Modern medicine applies variety of imaging techniques of the human body. The group of electro biological measurements comprises items as Electrocardiography (ECG, heart), electromyography (EMG, muscular contractions), Electroencephalography (EEG, brain), magneto encephalography (MEG, brain), Electrogastrography (EGG, stomach), Electrooptigraphy (EOG, eye dipole field). Imaging techniques based on different physical principles include computer tomography (CT), magnetic resonance image (MRI), functional MRI (FMRI), position emission tomography (PET) and single photon emission computed tomography (SPECT).

II. SURVEY ANALYSIS OF LIPSCHITZ EXPONENT

In this paper [14] the method described deals with the problems of T-wave detection in an ECG.

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Determining the position of a T-wave is complicated due to the poor amplitude, the ambiguous and changing form the complex. A wavelet transforms approach handles these complications therefore a method developed based on this concept. By this method we developed a detection method that is able to detect T-waves with a sensitivity of 93% and a correct detection ratio.

In bio signal, the existence of faults usually produces transient signatures that can be treated as singularities. Thus a signal processing technique that ignores the regular part of a signal and focuses on the transient part should have more potential in characterizing these fault-related components. Mallat and Hwang explored this problem and they proposed singularity detection with wavelet method. According to their conclusions, most of the useful information in a signal is contained in the local maxima of the continuous wavelet transform modulus. By examining the asympltotic decay of wavelet modulus maxima from coarser scale to finer scale, the strength of the singularity can be characterized by Lipschitz exponent α , or Holder exponent in some other literatures.

In this paper [12] the purpose of feature extraction is to abstract substantial information from the original data input and filtering out redundant information. In this paper we transfer the Hyper spectral data from the original-feature space to a scale-space plane by using a wavelet transform to extract significant spectral features. The wavelet transform can focus on localized signal structures with a zooming procedure. The absorption bands are thus detected with the wavelet transform modulus maxima, and the Lipschitz exponents, are estimated at each singularities point of the spectral curve from the decay of the wavelet transform amplitude. The local frequency variances provide some useful information about the oscillations of the hyper spectral curve for each pixel. Different type of materials can be distinguished on the basis of the differences in the local frequency variation. The new method generates more meaningful features and is more stable than other known methods for spectral feature extraction.

In this paper [6], the paper concerns the problem of the application of the Discrete Wavelet Transform and the Lipschitz exponent to an estimation of function differentiability. The influence of number of discrete data (measurements points) and a class of function on the discontinuity indicator is analyzed. The problem is discussed on the example of functions which represent a structural response of a mechanical static system.

In this paper [13], the proper description of the electroencephalogram (EEG) often requires simultaneous localization of signal's structures in time and frequency. We discuss several time-frequency methods as follows windowed Fourier transform, wavelet transform (WT), wavelet packets, wavelet networks and Matching Pursuit (MP). Properties of orthogonal WT are discussed in detail. Advantages of wavelet parameterization, including fast calculation of band-limited products are demonstrated on an example of input preprocessing for feed forward neural network learning detection of EEG artifacts. MP algorithm finds sub-optimal solution to the problem of optimal linear expansion of function over large and redundant dictionary of waveforms. We construct a method for automatic detection and analysis of sleep spindles in overnight EEG recordings, based upon MP with real dictionary of Gabor functions. Each spindle is described in terms of natural parameters. In the same way the slow wave activity (SWA) is parameterized. In this framework several of reported in literature hypotheses, regarding spatial, temporal and frequency distribution of sleep spindles, and their relations to the SWA, are confirmed. We present also an application to automatic detection and spatial analysis of superimposed spindles. Finally, owing to its high sensitivity, proposed approach allows the first insight into the issue of low amplitude spindles, undetectable by the methods applied up to now.

In this paper [11], the method described deals with the problems of singularity measurements using wavelets, due to the low amplitude, the ambiguous and changing form of the complex. A wavelet transform approach handles these complications therefore a method based on this concept was developed. The new method generates more meaningful features and is more stable than other known methods for spectral feature extraction.

III. ELECTROENCEPHALOGRAPHY (EEG)

Electroencephalographic measurements are commonly used in medical and research areas. This review article presents an introduction into EEG measurement. During more than 100 years of its history, encephalography has undergone massive progress. The existence of electrical currents in the brain was discovered in 1875 by an English physician Richard Caton observed the EEG from the exposed brains of rabbits and monkeys.

A. BRAIN WAVES CLASSIFICATION

The best-known and most extensively studied rhythm of the human brain is the normal alpha rhythm. Alpha can be usually observed better in the posterior and occipital regions with typical amplitude about 50 μV (peak-peak). According to our experiences alpha was also significant between posterior and central regions in comparison to other regions. Alpha activity is induced by closing the eyes and by relaxation, and abolished by eye opening or alerting by any mechanism (thinking, calculating). Most of the people are remarkably sensitive to the phenomenon of "eye closing", i.e. when they close their eyes their wave pattern significantly changes from beta into alpha waves. The precise origin of the alpha rhythm is still not known. Alpha waves are usually attributed to summated dendrite potentials. Evoked potentials (e.g. generated in brain stem) often consist of fiber potentials (axional) and synaptic components.

Brain waves have been categorized into four basic groups

1. Beta (>13 Hz),
2. Alpha (8-13 Hz),
3. Theta (4-8 Hz),
4. Delta (0.5-4 Hz)

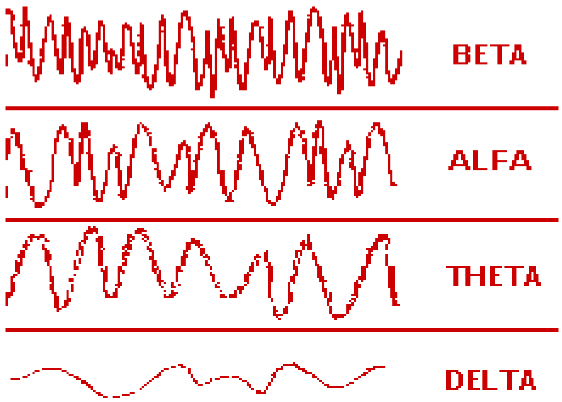

Figure .3.1 Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta band.

IV. MEASUREMENT OF LIPSCHITZ EXPONENT USING WAVELET TRANSFORM MODULUS MAXIMA

The Lipschitz exponent is a well known tool, which is used to estimate of function differentiability. To find function discontinuity, the exponent is applied together with wavelet transform. For better understanding of our paper, basis of wavelet transform and the Lipschitz exponent are shortly presented below. The possibility and suitability of function discontinuity estimation using. Discrete Wavelet Transform (DWT) is discussed in the paper.

A problem of number and density of the data arises because the DWT uses a discrete data representing a function. The problem is analyzed for various classes of function and the results are compared to analytical solutions.

A. LIPSCHITZ EXPONENT MEASUREMENT STEPS

1. Compute straight line l (log2(s)) connecting (log2(s small), log2| Wf (u, s small)|) and (log2 (smax), log2|Wf (u, s max)|). If l (log2(s)) ≥ log2| Wf (u, s)|, return the intercept log2 (A) and slope α of l (log2(s)), go to 7), otherwise, go to 2).
2. Let s=smax and f (A, α) = C, where C is a constant large enough.
3. Compute tangent l (log2(s)) at (log2(s), log2|Wf (u, s)|). If l (log2(s)) ≥ log2|Wf (u, s)|, go to 4). Otherwise go to 6).
4. Compute, record the result f and the inter-cept log2 (A) and slope α of l (log2(s)). If f <f (A, α), f (A, α) = f and LE = α.
5. If s = smin, go to 7). Otherwise go to 6).
6. s =s-Δlog2(s), go to 3.
7. Output LE = α.

V. RESULTS

The wavelet transform is particularly well adopted to estimate the local regularity of function. When a function is approximated at a finite resolution, strictly speaking, it is not meaningful to speak about singularities, discontinuities and Lipschitz exponents. This is illustrated by the fact that we cannot compute the asymptotic decay of the wavelet transform amplitude at scales smaller than one. In this work we used the function f(x) shown in Fig.5.1 which will be used for testing the capabilities of the wavelet to determine the regularity.

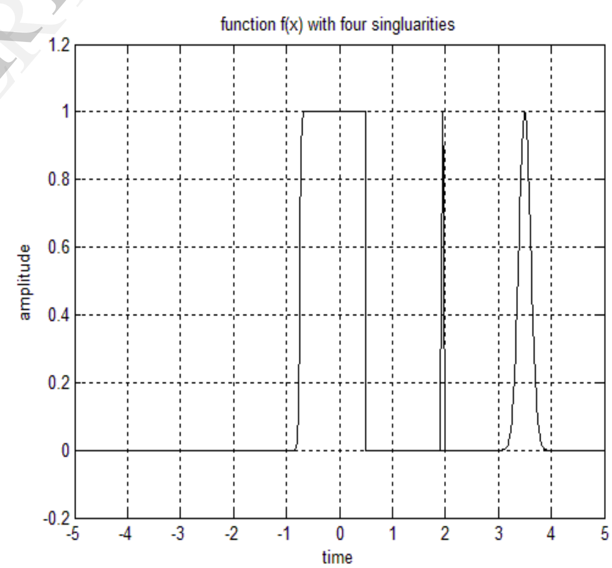

Figure.5.1. Function f(x) with four singularities at abscissa 413, 551, 696, and 802

Continuous Wavelet transform of function f(x) shown in Fig.5.2. The discontinuity appears clearly from the fact that |Wf(s, x)| remains approximately constant over a large range of scales, in the neighborhood of the abscissa 551. A negative Lipschitz exponent corresponds to sharp irregularities where the wavelet transform modulus increases at fine scales.

At the abscissa 696, the signal of Fig5.2 has such a discrete Dirac. The wavelet transform maxima increase proportionally to s^{-1}, over a large range of scales in the corresponding neighborhood.

The log-log plot of scale s versus WTMM (blue color) shown in Fig.5.3 with tangent line (Red color), then to find the slope of corresponding scale and coefficient line using Lipschitz Exponent (α) measurement procedure.

The adopted wavelet ψ(x) is the second initialization of A and α can be avoided.

The adopted wavelet ψ(x) is the second derivative of a Gaussian function. We denote $S_{small}=2$

$S_{max}=128$ and $\Delta\log2s=0.0326$, and for this method we adopt the initial function values A=2 and α=1.

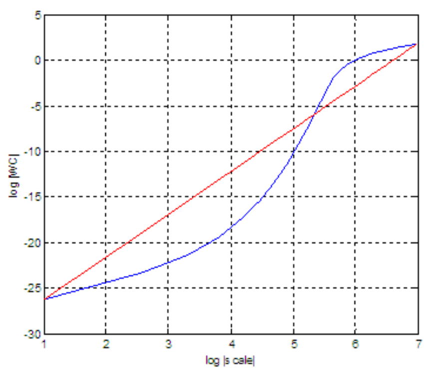

Figure.5.2.Log - log plot of scale s versus WTMM with tangent line

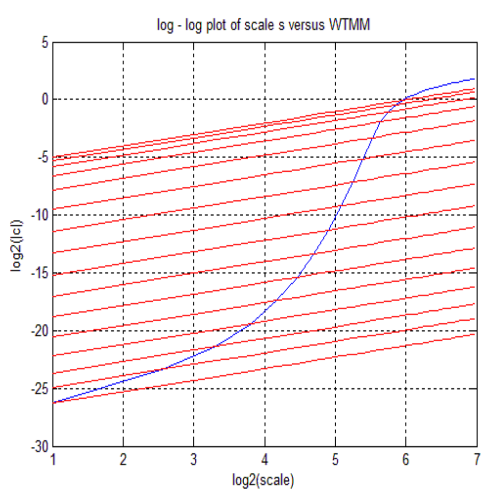

Figure.5.3.log2 – log2plot of scale s versus WTMM with tangent line

The log-log plot of scale s versus WTMM (blue color) shown in Figure.5.4. with tangent line (red color), then to find the slope of corresponding scale and coefficient line using lipschitz exponent (α) measurement procedure.

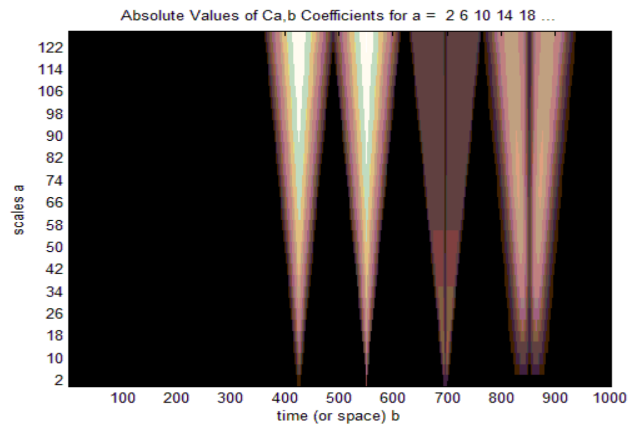

Figure.5.4. Continuous Wavelet transform of function f(x)

The use of the Interscale ratio method provides a simple means to select the wavelet coefficients that correspond to the regular parts of the signal. This effect is more obvious for those irregular signals that have $-1 < \alpha < 0$. Since, for these signals, the sum of the modulus of their wavelet coefficients will also increase as the scale increases. The only difference of them from a regular signal is that they have slower increasing rates. We determined Lipschitz exponent function (α) and compare with results of other works in Table.5.1. LE with objective function is more accurate value. Because we use the appropriate known edge of α, algorithm searches the Optimal result along $\log_2|Wf(u, s)|$ curve only and the problem of initialization of A and α can be avoided.

Table 5.1 Comparison Of LE (A) With Hawang And Objective Function.

S.NO	SINGULARITY AT ABSCISSA	LE IN [1] HAWANG	LE IN OBJECTIVE FUNCTION
1	413(-0.92)	2.4497	1.1659
2	551(0.5)	0	0.0049
3	696(2)	-0.1669	-0.0320
4	802(3.5)	2.3635	0.7513

CONCLUSION

Thus it has proved that the wavelet transform modulus maxima detect all the singularities of a function and we described strategies to measure their Lipschitz regularity. This mathematical study provides algorithm for characterizing singularities of irregular signals such as the multiracial structures observed in physics. We use the area between the straight line was satisfied and the curve of WTMM in a finite scale interval in the log-log plot of scale s versus WTMM as the objective function. The exponent results demonstrated out algorithm had better precision and robustness.

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