Spectral analysis of stabilographic signals by Fourier and Hilbert – Huang methods

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Spectral analysis is an important pipeline step in digital signal processing and significantly effects on received information. Methodical distortions in the information leads to corruptions of properties contained in the signal, and these is an origin of mistaken analysis. The Fourier transform is widespread as such pipeline step, but it limited for processing non-stationary and nonlinear signals. The spectral analysis of the Hilbert-Huang transform has no such limits. The transform is based on the Hilbert spectrum and empirical mode decomposition. The research is focused on the application of the Hilbert-Huang transform to stabilogram data analyses. The method to exarticulate the control factor of the human stability mechanism is developed.

Keywords- Hilbert-Huang transform, empirical mode decomposition, Fourier transform, stabilogram, spectral analysis

I. INTRODUCTION

Stabilometry becomes a more widespread treatment for clinical diagnostics. Maintaining balance is the abbility to keep veritcal pose of the body during standing, and it is a dynamic process. Depending on the environmental and physical conditions the body of a standing person performs oscillatory movements with greater or lesser amplitude in various planes. The characteristic of these oscillations reflects the state of the various systems involved in maintaining balance. As well as evaluation of the motor functions of patients after a stroke to define harmed sensor systems. It is known that the equilibrium of the human body controls by vestibular, visual, and sensory systems. So, the process of keeping a human's balance can be proposed as a superposition of oscillation on different frequencies and different origin. Moreover, according to frequencies, the control factor of balance can be determined. Spectral analysis is a mathematical assessment of the oscillations of the general center of pressure. In addition, according to the frequencies, the system involved in maintaining balance can be determined.

According to previous research [1] the highest frequency oscillations are associated with ankle movements and proprioceptive signals, and the total spectral energy is low-frequency body oscillations. In the research, the spectrum was divided into three intervals 0–0.5 Hz, 0.5–2 Hz, and 2–20 Hz. According to researches [2, 3] low frequencies (before 0.1 Hz) are associated with visual control, mid-low frequencies (0.1 – 0.5 Hz) are associated with vestibular reflexes, mid-high frequencies (higher than 0.5 Hz) are associated with somatosensory activity, and high frequencies are associated with the central nervous system. Additionally, in the research [5] was shown that low frequencies (before 0.5 Hz) are mainly responsible for visual-vestibular regulation, medium frequencies (0.5 - 2 Hz) are responsible for cerebellar regulation, and high frequencies (higher than 2 Hz) are responsible for proprioceptive regulation. Therefore, spectral decomposition of the signal specifies the quality of the analysis.

Fourier analysis is widespread for stabilometry data. But there are limitations of the method such as linearity and stationarity of the data. Thus, the Fourier transform can be applied to the analysis of stationary signals whose statistical characteristics are known at a constant time interval. From the point of view of the analysis of non-stationary signals, there are significant limitations of informativeness. The exact behavior of the non–stationary signals is unknown over the time and it is impossible to determine whether it is square integrable or absolutely integrable, which requires for the Fourier transform. Our proposed empirical mode decomposition-based method outperforms the conventional Fourier method [6].

On the other side, the human body's oscillations are by nature of the result of a dynamic system with various feedbacks [7]. Such understanding of the signal origin refutes a hypothesis of the data linearity and stationarity. Consequently, the correctness of the usage of the Fourier analysis raises the issue.

The empirical mode decomposition (EMD) offers a potential solution for such limits. EMD is based on SIFT algorithm and a data-adaptive decomposition that separates a signal into a set of intrinsic mode functions (IMFs). In return, the IMFs permit physically interpretable by Hilbert transforms [8]. In the research, Hilbert-Huang transformation is used. The EMD decomposes the signal into a number of empirical modes (EM) [9]. Then the Hilbert-Huang transformation can be based on the construction of the Hilbert spectrum using EMs. The keynote idea of the method is to construct the basis functions of the signal, which are formed adaptively from the input data. Each IMF can be analyzed in terms of its instantaneous frequency characteristics at the full temporal resolution of the dataset [10]. Decomposition of the amplitude modulations of each IMF describes signal energy across carrier frequency, amplitude modulation frequency and time [11].

The purpose of the study is to develop a method of stabilometry data analyses using EMD and the Hilbert-Huang spectrum.

II. Materials and Methods

So, input data is a signal with a certain frequency and can be described as:

$$\left\langle \vec{x}(t), f \right\rangle \quad (1)$$

where **x**(t) is a vector of x(t) and y(t) coordinates from stabilogram device, *f* – is a signal frequency.

After EMD the initial signal can be presented as:

$$\vec{x}(t) = \sum_{j=1}^{N} \vec{c}_j + \vec{r}_N \quad (2)$$

where $\mathbf{c}_j(t)$ is an EM, and $\mathbf{r}_N$ – the residual function.

The decomposition was provided for each vector component. Therefore, the original signal is presented by the sum of EMs and the residual function. Each EM is characterized by an oscillatory process with a certain frequency inherent in the original data. The residual function shows the trend contained in the original data.

The main purpose of the Hilbert transform is to determine a unique, analytic signal (3) from a real signal to calculate instantaneous properties (4), (5). The algorithm for obtaining the instantaneous values of the signal lies in the fact that, if a complex signal is determined, it is possible to extract the amplitude (6) and phase (7). Both characteristics depend on time, that's why they are called instantaneous. To calculate the Hilbert spectrum, it needs to calculate the instantaneous energy (4) and the instantaneous frequency (5) of the signal.

$$z(t) = x(t) + iH\{x(t)\}, \quad (3)$$

$$e = |A(t)|^2, \quad (4)$$

$$\omega(t) = d\varphi(t)/dt. \quad (5)$$

$$A(t) = (x^2(t) + H\{x(t)\}^2)^{1/2}, \quad (6)$$

$$\varphi(t) = \arctan(H\{x(t)\}/x(t)), \quad (7)$$

After performing the Hilbert transform on each IMF component, the original data can be expressed as the real part in the following form:

$$x(t) = \operatorname{Re} \sum_{j=1}^{N} a_j(t) \cdot Exp\left(i \int w_j(t) dt\right) \quad (8)$$

A detailed EMD algorithm and the origin of equations (3) – (7) are given in [8]. The IMFs' decomposition algorithm is presented below.

Algorithm 1

Input: f(t) – signal data;

Output: IMF(k) – number of IMFs;

res(t) = f(t)

I(1) = res(t)

i = 1, k = 1

while res(t) $\neq$ 0 or res(t) is not monotone **do**

  while I(i) has non – negligible local mean **do**

    Eup(t) = spline through local max of I(i)

    Elow(t) = spline through local min of I(i)

    Emean(t) = 1/2(Eup(t) + Elow(t))

    I(i) = I(i) – Emean(t)

    i = i + 1

  end while

  IMF(k) = I(i)

  res(t) = res(t) – IMF(k)

  k = k + 1

end while

As a result of Hilbert spectral decomposition, the original data can be presented in energy-time-frequency terms. To analyze the stabilogram data in the energy-time domain the Hilbert spectrum data was reduced by frequencies. Based on the physiological origin [2, 3, 4] of the oscillations the frequency domain was divided into the following intervals: 0 - 0.1 Hz, 0.1 - 0.5 Hz, 0.5 - 2 Hz. The Hilbert spectrum data were integrated for each interval by frequency domain.

This transform allows associating origin data with three energy-time spectrums. Each spectrum is based on the frequency interval and can be understood as a response to a certain type of feedback. Viz namely there are visual control, vestibular reflexes, and somatosensory activity, respectively to intervals.

Algorithm 2

Input: data

Output: sAm(i), sTime(i)

where i – number of interval

IMF = EMD(data)

[Am, Fr, Time] = HHT(IMF)

for each frequency interval **do**

  [sAm(i), sTime(i)] = integrate([Am, Time])

end for

Traditionally in the Fourier analysis for stabilometric data, the following parameters are used [3]: average and maximum amplitudes, the percentage contribution of power, the absolute power value of the power spectrum, as well as 60% of the power in the entire range under consideration.

The depersonalized dataset of stabilometry was used. Subjects stood for 1 min with open eyes and for 1 min with closed eyes during the measurements. The sagittal oscillations for open and closed eyes were analyzed by both methods. The implementation of the methods was carried out in MATLAB software.

III. Results

Stabilometry data was processed by Fourier analyses and proposed method. Average amplitude was calculated for each frequency interval. Hilbert spectrum in the energy-time domain is presented in Figure 1.

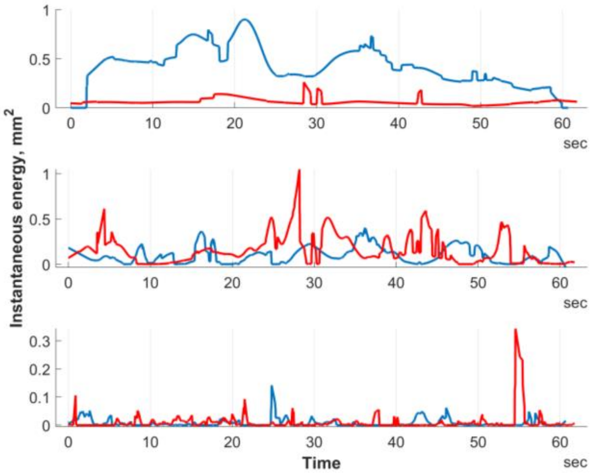

Fig.1. Hilbert spectrum in the energy-time domain for frequency intervals (top-down), the blue line is for open eyes case, the red line is for close eyes case.

The average amplitudes were calculated for the Hilbert spectrum and compared with Fourier analysis results. In Figure 2 confidence intervals are presented. The confidence intervals for the Hilbert spectrum are narrow that is why results are presented in log-axes.

Using Fourier analysis, there were no significant difference between average amplitudes in all frequency intervals – amplitudes scatter a lot in the frequency intervals. On the opposite, using the proposed method there was a significant difference between average amplitudes in the 1st and 2nd frequency intervals. But there was no significant difference in the 3rd frequency interval.

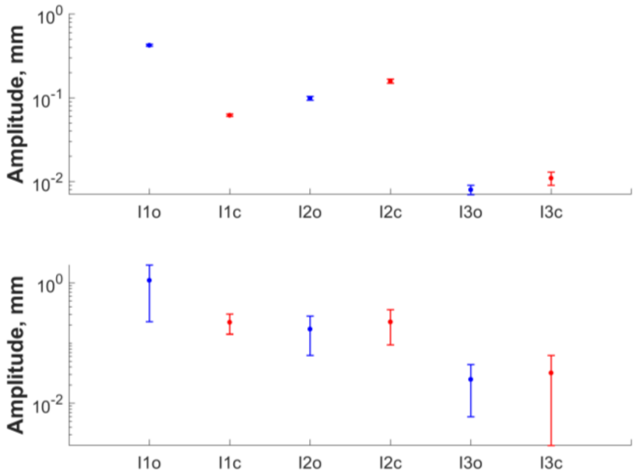

Fig.2. Confidence intervals for average amplitude in frequency intervals for Hilbert and Fourier spectrum (top-down), the blue line is for open eyes case, the red line is for close eyes case.

To compare the open and close eyes cases the cross-correlation was calculated for Hilbert spectrum (see Figure 3).

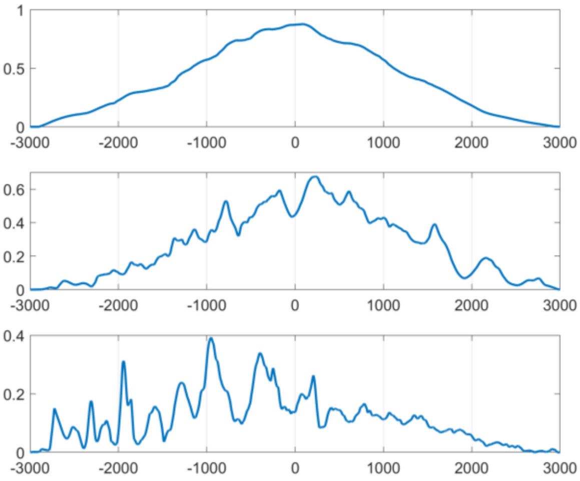

Fig.3. Cross-correlation of open and close eyes Hilbert spectrum in the energy-time domain for frequency intervals (top-down).

It can be noticed that despite the significant difference between average amplitudes the cross-correlation is high for the 1st and 2nd frequency intervals. It can be explained that the amplitude-time behavior for the 1st and 2nd frequency intervals is similar. The difference between the amplitude-time behavior for the 1st and 2nd frequency interval is in the scale factor. Meanwhile, the cross-correlation for the 3rd frequency interval is low.

IV. Discission

There was no difference between amplitudes in the 1st and 2nd frequency intervals for open and close eyes cases, in terms of Fourier analysis. On the opposite, the proposed method shows the significant difference between amplitudes in the 1st and 2nd frequency intervals for open and close eyes cases. The average amplitude is much higher for the 1st frequency interval in the case of open eyes. And the average amplitude is much higher for the 2nd frequency interval in the case of close eyes. Since, the slightest changes in posture are induced by visual, vestibular, and somatosensory receptors and this afferent information enters the central nervous system [12, 13, 14, 15]. Then an immediate response occurs, as a result of which afferent information from various levels of the central nervous system corrects the postural command. That leads to the correct position by changing muscle tone in the appropriate muscle groups [14, 15, 16].

It was aforementioned that frequencies before 0.1 Hz are associated with visual control, frequencies in the interval from 0.1 to 0.5 Hz are associated with vestibular reflexes, and frequencies higher than 0.5 Hz are associated with a somatosensory activity [2, 3]. It can be seen that the amplitude values when the visual system is involved are much greater than when it is absent, because of the difference in amplitudes in the 1st and the 2nd frequency intervals. This is due to the fact that a person with open eyes uses the visual system to balance the body. Otherwise, a person with closed eyes uses vestibular reflexes to balance the body. So, the results illustrate the ability of the proposed method to diagnose the control factor of the humans balancing is developed.

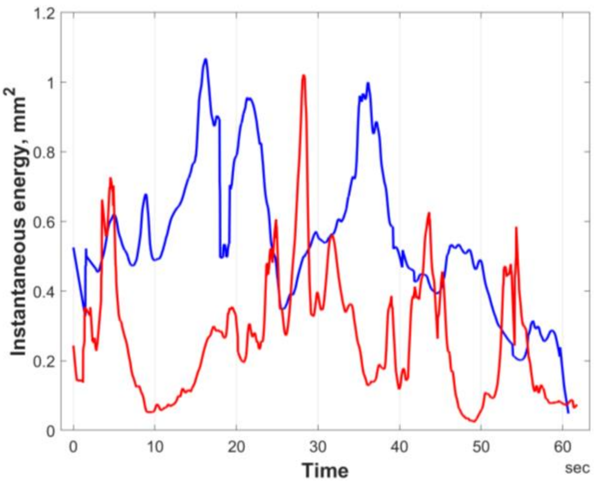

Fig.4. Hilbert spectrum in the energy-time domain for whole frequency interval, the blue line is for open eyes case, the red line is for close eyes case.

Analyzing the Hilbert spectrum data in the amplitude-time domain for whole frequency interval (Fig. 4) the oscillatory processes occurred during the human standing can be concluded. The highest frequencies with pronounced energy occurs (see Fig. 1 and Fig. 4) in the first seconds, which is explained by the establishment of equilibrium at the start of the experiment. It is noticeable that from the middle of the experiment, the energy value begins to increase again. Over time, the balance begins to break, as there is slight fatigue and the amplitude of the oscillations increases. To balance the body, an ankle strategy begins to be used, helping to restore the common center of mass by movements in the ankle joints, which activate the muscles in the ankles, knees and hip.

V. CONCLUSIONS

So, the method for analyzing the stabilometry data is proposed. The method is based on EMD and the Hilbert-Huang spectrum. Method for reducing the energy-time-frequency domain of Hilbert spectrum to energy-time is developed. The technique to find out the control factor of the humans balancing frequencies intervals was introduced. The depersonalized dataset of stabilometry was used to verify the method. The sagittal oscillations for cases of open and closed eyes were analyzed. The method was compared with Fourier analysis, the principal differences in the result were shown. The proposed method allows the automation of the analysis and illustrates the high quality of the received results.

VI. ACKNOWLEDGEMENT

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