EEG SIGNAL ANALYSIS BASED ON EMD AND DISCRETE ENERGY SEPARATION ALGORITHM

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Abstract: This paper deals with spectral analysis of nocturnal EEG signal from apnoea/hypopnea patients. Main goal is to employ methods independent to Fourier Transform, because of nonstationary character of signal, to better description of frequency changes. For this purpose, analysis based on Empirical Mode Decomposition and Discrete Energy Separation Algorithm was tested. This method is similar to commonly used Hilbert Huang Transform, but can provide higher time and frequency resolution due to algorithms based on Teager-Keiser Energy Operator, which can work with very short time window.

Keywords: nocturnal EEG, Empirical Mode Decomposition, Teager-Keiser Energy Operator, Discrete Energy Separation Algorithm

1. INTRODUCTION

Nowadays, there are still some unsolved tasks in electroencephalogram (EEG) analysis, especially in frequency and time-frequency domain. Due to the considerable non-stationary and nonlinear character of EEG, commonly used methods based on Fourier transform (FT) provide the resulting frequency spectrum with only little physical sense [1]. Therefore, several methods to analyse spectrum of such signals have been developed in past decades.

Hilbert Huang Transform (HHT) is one of these methods. HHT is based on empirical mode decomposition (EMD), followed by Hilbert transform to compute Hilbert spectrum [1]. This method forms a significant inspiration for our work. The main goal was to replace rather difficult Hilbert transform with simpler frequency determination method. Discrete Energy Separation Algorithm (DESA) can be considered as such [2], [3].

Implemented methods are described in Chapter 2. Chapter 3 considers practical use on real EEG signal.

2. METHODS

2.1. EMPIRICAL MODE DECOMPOSITION

EMD is an empirical method used to decompose a multicomponent signal into a number of signal components in the time domain called intrinsic mode functions (IMF). Each IMF represents a bandwidth of frequencies of the signal, so the EMD method can be used for removing unwanted components of the signal being analysed. Linearity of this method can be considered as strong aspect, as well as decomposition based on signal character and not just on uniform frequency bandwidths [1], [2].

The EMD procedure for extracting IMF is called the *sifting process* and consists of the following steps [1], [2]:

- finding of local maxima and local minima of signal *x(t)*,
- constructing of upper (maxima) envelope *u(t)*, and lower (minima) envelope *l(t)*,
- estimation of mean envelope $m_1(t)$ as a mean value of *u(t)* and *l(t)*, then first possible component is given by the equation $h_1(t) = x(t) - m_1(t)$.

The component $h_1(t)$ is accepted as the first IMF only if two conditions are satisfied. First, the number of extrema and the number of zero crossings over the entire length of the IMF must be equal or differ at most by one, and second, at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. Otherwise $h_1(t)$ is treated as the new data set and $m_{11}(t)$ is estimate, that is used to calculate $h_{11}(t)$. The *sifting process* is repeated until the component $h_{1k}(t)$ is accepted as an IMF of the signal *x(t)* and is denoted by $C_1(t)$

$$C_1(t) = h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t). \tag{1}$$

- IMF is subtracted from original signal *x(t)* resulting residual signal $r_N(t)$. After that, *sifting process* repeats with residual signal as input. The process ends when the last residual signal, $r_N(t)$ is obtained and it is a constant or a monotonic function.

2.2. DISCRETE ENERGY SEPARATION ALGORITHMS

These algorithms are based on the Teager-Kaiser Energy Operator (TKEO). Assume that TKEO for discrete case is [3]:

$$\psi[x(n)] = x^2(n) - x(n-1)\cdot x(n+1) \approx A^2\omega^2, \tag{2}$$

where $x(n) = A\cdot\cos(\Omega(n))$ is input signal with amplitude *A* and $\Omega(n) = \omega\cdot T_s$ (T_s – sampling period) according to [3].

TKEO offers excellent time resolution, because only three samples are required for the energy computation at each time instant. From (4), it is obvious that TKEO reflects not only amplitude of analysed signal, but also its instantaneous frequency $\omega = 2\pi f$. Based on this knowledge, DESA algorithms can be estimated [2], [3].

First DESA-2 algorithm, where ‘2’ implies the approximation of first-order derivatives by differences between samples whose time indices differ by 2, estimates time varying frequency and amplitude envelope according to [3], as:

$$\Omega(n) \approx \arcsin\left(\sqrt{\frac{\psi[x(n+1)-x(n-1)]}{4\cdot\psi[x(n)]}}\right);\ |A(n)| \approx \frac{2\cdot\psi[x(n)]}{\sqrt{\psi[x(n+1)-x(n-1)]}} \tag{3}$$

By implementation of *arcsin (u)*, usage of DESA-2 was limited to frequencies ≤ *1/4* of the sampling frequency (assumes that $|u| \le \pi/2$).

An alternative is DESA-1 algorithm, which according to [3] replaces derivatives with backward and forward differences:

$$y(n) = x(n) - x(n-1),\ y(n+1) = x(n+1) - x(n), \tag{4}$$

such replacement yields new estimations as

$$\Omega(n) \approx \arccos(G(n)),\ |A(n)| \approx \sqrt{\frac{\psi[x(n)]}{1-G^2(n)}}, \tag{5}$$

where

$$G(n) = 1 - \frac{\psi[y(n)] + \psi[y(n+1)]}{4\cdot\psi[x(n)]}, \tag{6}$$

which provides benefits within frequency range ≤ *1/2* of the sampling frequency (*arccos (u)*) and according to previous studies slightly lower error rate [3].

DESA-1 algorithm in theory can be considered as significant improvement compared to DESA-2. In this study, both algorithms were tested.

2.3. EMD – DESA SPECTROGRAM

Final algorithm combines EMD and DESA to compute amplitude 'spectrogram' of EEG signal. First, entering segment of EEG was decomposed to various number of IMFs based on conditions mentioned in chapter 2.1. Then DESA algorithm to estimate instantaneous frequency and amplitude characteristics for each IMF was applied. Finally, spectrogram matrix was constructed based on instantaneous frequency, amplitude and time position from each IMF for the same EEG segment.

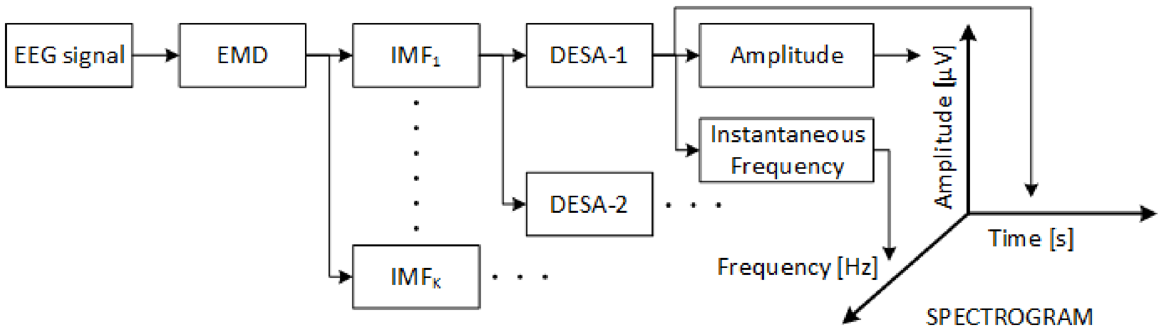

Figure 1: Calculation of spectrogram using EMD – DESA algorithm diagram

Mentioned algorithms were tested on real EEG signals from nocturnal polysomnographic examination of patients with sleep apnoea/hypopnea. All EEGs were sampled with frequency $f_s = 256\,Hz$ and filtered (lowpass at 70 Hz, highpass at 0.3 Hz and notch filter at 50 Hz). As additional pre-processing, another filtration with bandpass filter (bandwidth 0.5 – 30 Hz) was used. Segments (sleep epochs lasting 30 s) of EEG signal with high power noise (mostly due to patient movement) and identified as unclassified by PSG expert were excluded from analysis.

Obtained spectrograms were compared with that calculated using short-time Fourier transform (STFT) with Hamming window of a length 256 samples and 50% overlap (Figure 4).

3. RESULTS

EEG epochs were processed by basic EMD algorithm (chapter 2.1). Number of outcome IMFs (Figure 2 - right) varies trough the phase of sleep and patients from 9 to 16. EMD provides data with less noisy and more homogeny character than original EEG (Figure 2 - left) except 1st and sometimes 2nd IMF usually representing high frequency noise.

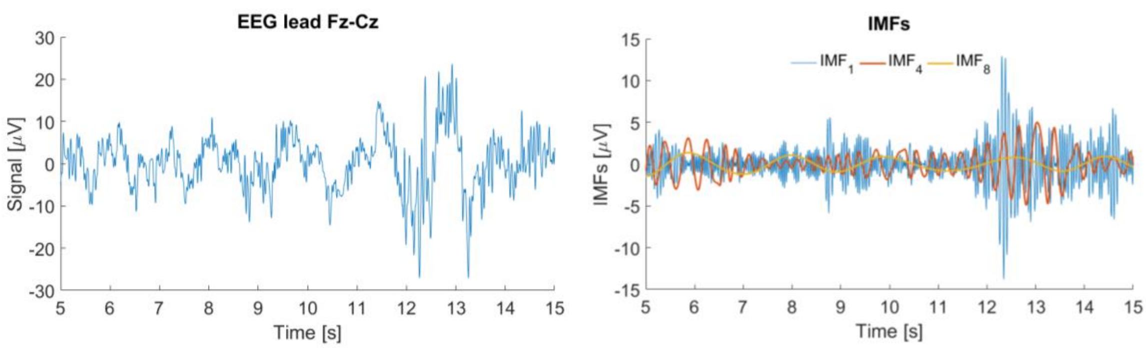

Figure 2: Detail of EEG segment and example of outcome IMFs

For each calculated IMF, instantaneous frequency and amplitude characteristics were estimated according to DESA algorithms (Chapter 2.2). DESA-1 and DESA-2 were tested. Because both of these algorithms works with 5-sample window, first and last two samples of epoch ware approximated by the closest value. Frequency precision was set on 0.1 Hz by simple rounding to one decimal place. Amplitude precision was set on 0.01 μV same way. DESA-1 and DESA-2 algorithms yield mostly same results with occasional local extremes.

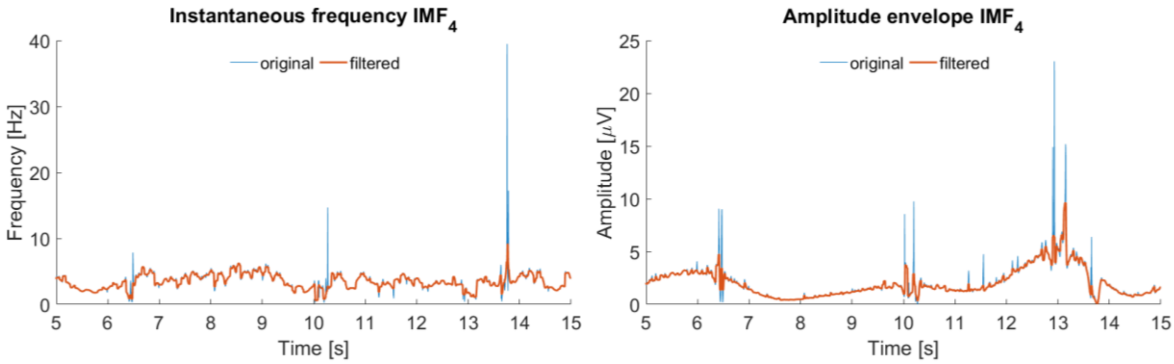

Figure 3: Detail of frequency and amplitude characteristics of IMF_4

After estimation of frequency and amplitude characteristics, final amplitude spectrogram (Figure 4) was created. To do that, frequency and time parts of IMF were used as the positions for x and y-axes, respectively. Amplitude values (z) were calculated as average values through all amplitudes associated with particular frequency and time instances. Median filtration (with 9 samples window) was applied as first choice to minimize mentioned local extremes (Figure 3, Figure 5).

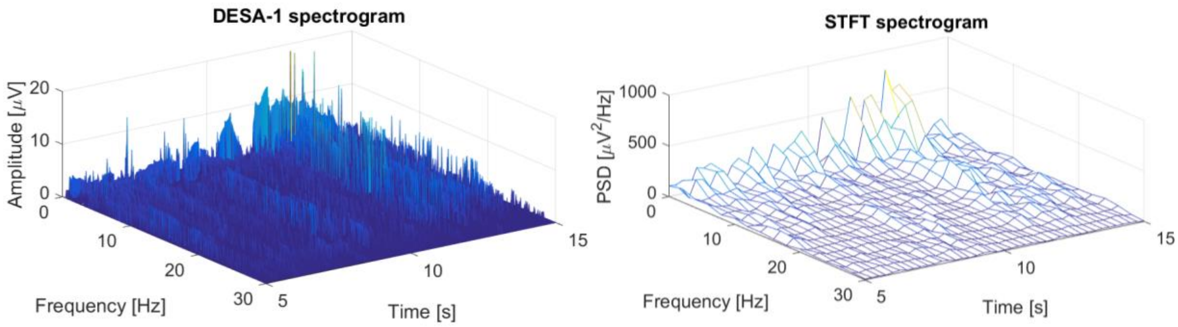

Figure 4: Detail of resulting EMD – DESA and STFT spectrograms

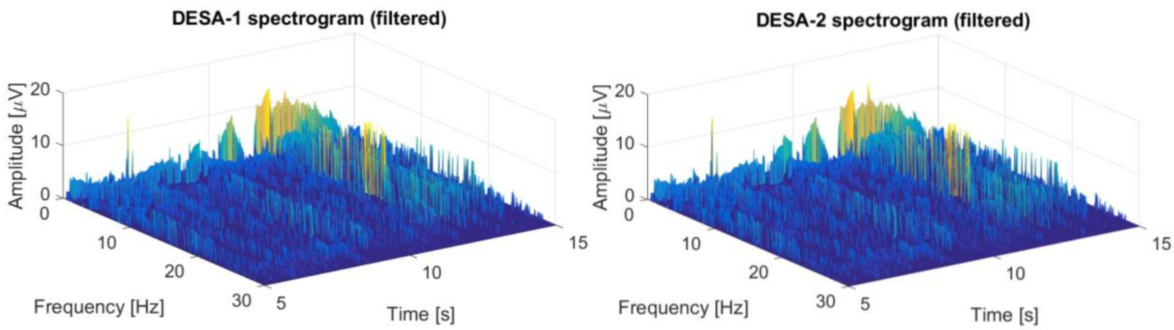

Figure 5: Detail of filtered EMD – DESA spectrograms

4. CONCLUSION

The problem of correct estimation of spectrogram for nonstationary signals was introduced. Main issue consists in use of Fourier Transform, which expects stationary harmonic signal as input. The EMD – DESA spectrogram can provide one of the possible solutions of this problem. In this paper, theoretical background and practical implementation of mentioned method were presented. From comparison of results obtained by EMD-DESA and STFT(Figure 4), it is evident, that both types of spectrograms have very similar character, even with different representation of z-axes. Nevertheless, EMD – DESA spectrogram provides higher frequency and time resolution compared with STFT spectrogram.

Mentioned benefits of proposed method can provide us powerful tool for time frequency analysis of nonstationary signals such as EEG. It may have great potential in such areas as automatic sleep stages recognition, where various parameters are calculated from EEG spectrogram and used as inputs for classification algorithm. High resolution of EMD-DESA spectrogram provides better localization of some important patterns, which correlates with different sleep phases (e.g. K-complexes, spindles, etc.). For example, low frequency components of original EEG (Figure 2) are better distinguished even in first 5 seconds of EMD – DESA spectrogram (Figure 5) opposite to STFT spectrogram (Figure 3) which suffers frequency leakage. Such quality can be crucial for reaching successful performance of sleep stages distinguishing, which is main objective of following study.

In other studies, DESA algorithms were successfully applied in speech analysis and multi-tone signal detection [3], [5]. Combination of EMD and DESA was tested in industry sector [2] and compared with HHT, where higher time resolution and less computation complexity of EMD – DESA spectrogram was confirmed. Main restrictions of method are limited frequency range (Chapter 2.2), occasional noisy character (Figure 4), and "low frequency error" [4]. As was shown above, noisy character of resulting amplitude and frequency characteristics can be supressed by simple filtration. Ensemble EMD (EEMD) can be applied in future to improve noise separation during decomposition process.

REFERENCE

[1] HUANG, N. E., Z. SHEN, S. R. LONG, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*. IEEE, 1998, 454(1971), 903-995. DOI: 10.1098/rspa.1998.0193. ISBN 0-7803-2127-8. ISSN 1364-5021

[2] ANTONIADOU, I., G. MANSON, W.J. STASZEWSKI, T. BARSZCZ a K. WORDEN. A time–frequency analysis approach for condition monitoring of a wind turbine gearbox under varying load conditions. *Mechanical Systems and Signal Processing*. 2015, 64-65(10), 188-216. DOI: 10.1016/j.ymssp.2015.03.003. ISSN 08883270

[3] MARAGOS, P., J.F. KAISER, T.F. QUATIERI, et al. On separating amplitude from frequency modulations using energy operators. [Proceedings] ICASSP-92: 1992 IEEE International Conference on Acoustics, Speech, and Signal Processing. IEEE, 1992, 454(1971), 1-4 vol.2. DOI: 10.1109/ICASSP.1992.226135. ISBN 0-7803-0532-9. ISSN 1364-5021

[4] LIPSEY, M.J., J.P. HAVLICEK, W.J. STASZEWSKI, T. BARSZCZ a K. WORDEN. On the Teager-Kaiser energy operator "low frequency error". *The 2002 45th Midwest Symposium on Circuits and Systems*, 2002. MWSCAS-2002. IEEE, 2002, 64-65(10), III-53-III-56. DOI: 10.1109/MWSCAS.2002.1186968. ISBN 0-7803-7523-8. ISSN 08883270

[5] VELEZ, E.F., J.P. HAVLICEK, W.J. STASZEWSKI, T. BARSZCZ a K. WORDEN. Detection of multi-tone signals based on energy operators. *Proceedings of IEEE-SP International Symposium on Time- Frequency and Time-Scale Analysis*. IEEE, 1994, 64-65(10), 229-232. DOI: 10.1109/TFSA.1994.467251. ISBN 0-7803-2127-8. ISSN 08883270