Multifractal analysis of real and imaginary movements: EEG study

Alexey N. Pavlov, Vladimir A. Maksimenko, Anastasiya E. Runnova, Marina V. Khramova, Alexander N. Pisarchik

Alexey N. Pavlov, Vladimir A. Maksimenko, Anastasiya E. Runnova, Marina V. Khramova, Alexander N. Pisarchik, "Multifractal analysis of real and imaginary movements: EEG study," Proc. SPIE 10717, Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV, 107171P (26 April 2018); doi: 10.1117/12.2311482

Event: Saratov Fall Meeting 2017, 2017, Saratov, Russian Federation

Multifractal analysis of real and imaginary movements: EEG study

Alexey N. Pavlov[a,b], Vladimir A. Maksimenko[a], Anastasiya E. Runnova[a,b], Marina V. Khramova[b] and Alexander N. Pisarchik[a,c]

[a] Yuri Gagarin State Technical University of Saratov, Politechnicheskaya Str. 77, Saratov 410054, Russia;
[b] Saratov State University, Astrakhanskaya Str. 83, Saratov 410012, Russia;
[c] Center for Biomedical Technology, Technical University of Madrid, Campus Montegancedo, 28223 Pozuelo de Alarcon, Madrid, Spain

ABSTRACT

We study abilities of the wavelet-based multifractal analysis in recognition specific dynamics of electrical brain activity associated with real and imaginary movements. Based on the singularity spectra we analyze electroencephalograms (EEGs) acquired in untrained humans (operators) during imagination of hands movements, and show a possibility to distinguish between the related EEG patterns and the recordings performed during real movements or the background electrical brain activity. We discuss how such recognition depends on the selected brain region.

Keywords: electroencephalogram; brain activity; brain-computer interface; pattern recognition

1. INTRODUCTION

The development of the brain-computer interfaces (BCIs) is a promising field in neuroscience, applied physics and technique. Specific dynamics of electrical brain activity is associated with "mental actions" being a compilation of imaginary commands. In order to reveal the related dynamics, a thorough analysis of multichannel EEG structure needs to be performed.[1–3] Such analysis should be provided in real time for simultaneous transmission of the revealed specific brain activity to control. The latter requires an accurate and precise recognition of EEG patterns taking into account their variability being typical for physiological systems. Besides, a person (operator) should be trained to reproduce specific mental states for their further recognition based on the multichannel EEG processing. Simple BCIs provide new perspectives of solving the problem of mental control.[4,5]

BCIs can be used as a different way for information input to computer by some categories of users, e.g., by humans with disabilities of motor functions.[6,7] An example is the BCI that was applied to move the cursor on computer screen by mental commands.[8] Such BCI was successfully used by a paralyzed patient to write simple phrases thus communicating with doctors.[8] Current progress in technology enables us supposing that BCIs will be widely applied in the nearest future to control artificial limbs, manipulators and robot-technical devices, in gaming industry, etc.[9,10]

The first step in BCI creation is to improve existing and to propose new effective methods for automatic recognition of specific EEG patterns associated with imaginary commands. The latter can be done using the approaches that analyze the time-frequency organization and the spatial structure of EEG such as the wavelet-analysis that has demonstrated its essential potential in solving the related problems.[11,12]

Here we study recognition abilities of a wavelet-based technique for multifractal analysis representing a powerful tools for statistical analysis of nonstationary and inhomogeneous processes. We consider an approach suggested by Muzy et al.[13,14] that use the continuous wavelet-transform for characterizing complex scaling phenomena in natural signals. This tool outperforms the earlier elaborated methods based on structure functions.[14] Main advantage consists in the possibility to study a wide range of singularities including small fluctuations in the signal that cannot be resolved with the structure functions approach.

Further information: (Send correspondence to A.N.P.) E-mail: pavlov.lesha@gmail.com, Telephone: +7 8452 998765

Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV, edited by Vladimir L. Derbov, Dmitry E. Postnov, Proc. of SPIE Vol. 10717, 107171P · © 2018 SPIE · CCC code: 1605-7422/18/$18 · doi: 10.1117/12.2311482

2. METHOD

The wavelet-transform modulus maxima (WTMM) method[13,14] includes two stages. At the first stage, the continuous wavelet-transform of a signal $x(t)$ is computed

$$W(a,u) = \frac{1}{a}\int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-u}{a}\right)dt, \tag{1}$$

where the parameters a and u characterize the scale and the translation of the wavelet-function ψ. A feature of the WTMM-method is that the normalizing factor is taken as $1/a$ instead of $1/\sqrt{a}$ mainly used in the wavelet-based studies to keep the energy of the function ψ at its dilations. This unusual normalizing factor is applied to simplify further estimations of the Hölder exponents. Another feature of the method is the insensitivity of the estimated singularity spectrum to the selection of the basic wavelet ψ. The latter allows us to use simple wavelets such as, e.g., WAVE or MHAT representing the first and the second derivatives of the Gaussian function. Higher derivatives which enable removing slow nonstationarity from the original signal $x(t)$ may also be used. Thus, if ψ has m vanishing moments, the wavelet transform (1) ignores a polynomial trend presented in the data up to the order m. Therefore, a preliminary filtering of slow nonstationarities becomes not necessary.

When the signal $x(t)$ is singular at a time moment u^*, e.g., it has n but not $n+1$ derivatives, then the appropriate selection of the wavelet ψ enables ignoring a regular part $P_n(t)$ obtained by the expansion of $x(t)$ into the Taylor series up to degree n, and the wavelet-transform will characterize only an irregularity of the analyzed process that can be described by a term $C|t-u^*|^h$ with h being the Hölder exponent.

Let us illustrate this property of the wavelet-transform using the signal $x(t)$ that has n derivatives at a point $t = u^*$ while the next derivative does not exist. The latter allows us representing this function in the vicinity of the singularity u^* as a sum of a regular part $P_n(t)$ obtained by the expansion of $x(t)$ into the Taylor series up to degree n, and an irregular part characterized by the Hölder exponent h

$$W(a,u^*) = C\int_{-\infty}^{\infty}\psi(t)|at|^{h(u^*)}dt \sim |a|^{h(u^*)}\int_{-\infty}^{\infty}\psi(t)|t|^{h(u^*)}dt. \tag{2}$$

As a result, the power-law dependence is obtained at small scales where neighboring singularities do not influence each other

$$W(a,u^*) \sim a^{h(u^*)}, \quad a \to 0. \tag{3}$$

This dependence enables computing the value of h associated with the singularity at the time moment u^*. Analysis of the wavelet-transform (1) provides a way to easily detect all singularity points because each point will lead to the appearance of a skeleton line, i.e., a line of the local maxima or minima of the wavelet-coefficients.

The second stage of the considered method includes estimations of the Hölder exponents and the singularity spectrum. Despite this estimation can be done from the power-law dependence (3), such approach is highly unstable due to the existence of neighboring irregular points that essentially change the related Hölder exponents. In order to provide a stable computing algorithm, partition functions are used

$$Z(q,a) = \sum_{l\in L(a)} |W(a,u_l(a))|^q, \tag{4}$$

with $L(a)$ and $u_l(a)$ being the full set of the revealed skeleton lines (their amount varies depending from the scale a), and the time moment when the maximum related to the line l appears. A consideration of modulus of $W(a,u)$ provides an additional improvements of the method's stability. A higher stability can be reached by excluding the case when $|W(a,u_l(a))|$=0, and $q < 0$

$$Z(q,a) = \sum_{l\in L(a)} \left(\sup_{a'\le a} \mid W(a',u_l(a')) \mid\right)^q. \tag{5}$$

The parameter q defines the considered range of singularities. Weak singularities associated with small fluctuations of the signal $x(t)$ are studied by selection negative q, and strong singularities related to large fluctuations are considered at positive q.

The partition functions are characterized by the following power-law behavior

$$Z(q,a) \sim a^{\tau(q)} \tag{6}$$

from which the spectrum of scaling exponents $\tau(q)$ is estimated. Further, the Hölder exponents $h(q)$ and the singularity spectrum $D(h)$ are computed

$$h(q) = \frac{d\tau(q)}{dq}, \qquad D(h) = qh - \tau(q).$$

Here, $D(h^*)$ is the Hausdorff dimension of a subset of data quantified by the Hölder exponent h^*. A typical singularity spectrum of an inhomogeneous complex process is shown in Fig. 1.

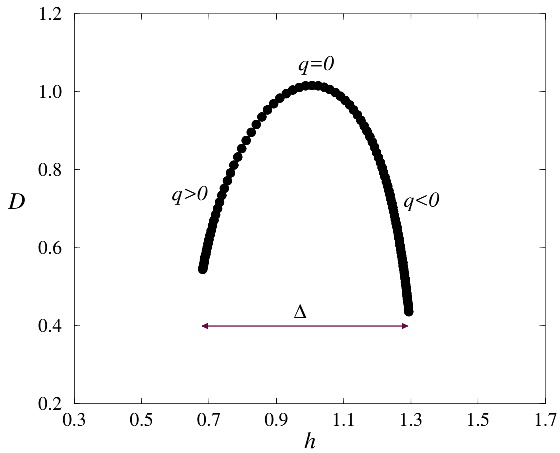

Figure 1. A singularity spectrum of an inhomogeneous complex signal

The shape of the $D(h)$ spectrum can be characterized by several quantities including: 1) the position of the singularity spectrum along the h-axis related to the value of $h(0)$ which reflects correlation properties of the analyzed signal; 2) the width Δ of the singularity spectrum quantifying the degree of inhomogeneity or complexity of the signal; 3) the asymmetry of the $D(h)$-spectrum reflecting distinctions of the scaling behavior for weak and strong singularities. Additionally, other quantities can be introduced reflecting, e.g., the ranges of the Hausdorff dimension separately for positive and negative q, distinctions in the ranges of the Hölder exponents for small and large fluctuations, etc.[15,16]

3. RESULTS

The method for multifractal analysis[13,14] was applied to analyze changes in the EEG recordings caused by real and imaginary hand movements as compared with the background EEG activity. For this purpose, movements of the right hand were repeatedly performed by 13 volunteers (25–35 years old). All experimental studies were conducted in accordance with the Helsinki Declaration of the World Medical Association. Each subject participated in one experiment lasting about 30 minutes. The experimental procedure included 10 sessions (5 sessions of real movements, and 5 – imaginary movements), with 20 repeated movements for each session. The movement (independently, real or imaginary) was started with a sound signal, and time intervals of 4 seconds after such signal were selected for the further analysis. Besides multichannel EEG recordings related to movements, a background electrical brain activity was acquired during 5 minutes at the beginning and at the end of each experiment.

The recording of EEG signals was carried out with the electroencephalograph Encephalan-EEGR-19/26 ("Medicom-MTD", Taganrog, Russia) using the standard setup 10-20. Singularity spectra were estimated for each movement and then averaged for each subject over a large number of repeated fragments of the same type (i.e., separately for real movements, imaginary movements and the segmented background EEG activity).

Analysis of the estimated $D(h)$-spectra did not revealed significant distinctions between real and imaginary movements, as well as between imaginary movements and the background EEG when considering such measures as the width of the singularity spectrum, its asymmetry or the range of the Hausdorff dimension. Although some distinctions were found, a strong variability of the estimated measures between different sessions did not enable authentic recognition of the related EEG-patterns. The most significant distinctions were revealed in the positions of $D(h)$-spectrum corresponding to mean Hölder exponents $H = h(0)$. Figure 1 illustrates these changes for the case of Cz-channel. Despite essential variability of H between different subjects, in each experiment an authentic separation between real and imaginary movements is observed. Thus, we can adjust the recognition algorithm to clearly detect changes in EEG patterns. Similar results are observed for other channels, i.e., the performed analysis confirms the recognition abilities of the used approach. Let us note that distinguishing between real and imaginary hand movements are easily detected using the value of H. It is also easily to separate between real movements and the background EEG-activity. The separation between the background EEG and the imaginary movements is possible, but not for all channels. For Cz-channel, for example, such separation was performed, although the distinctions for C3-channel were insignificant.

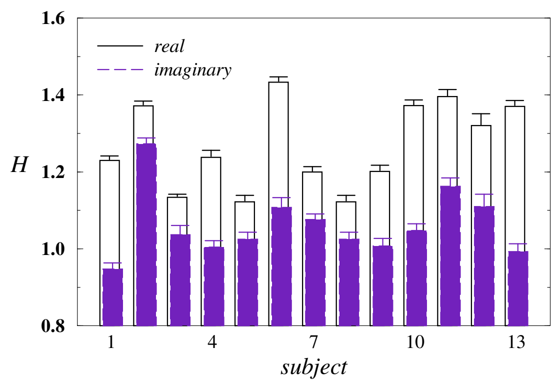

Figure 2. Separation between real and imaginary movements of the right hand. Data are shown as mean ± SE.

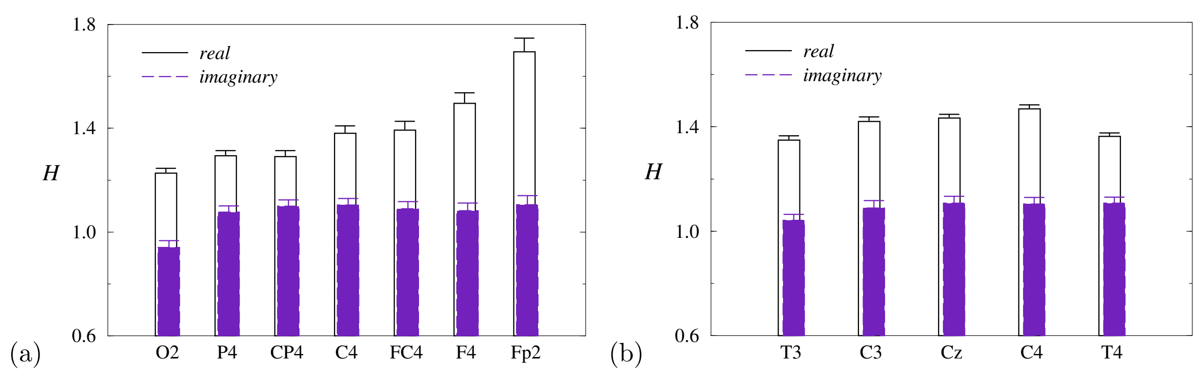

Figure 3. Distinctions between real and imaginary movements of the right hand related to EEG-channels selected from the back of the head to the forehead (a), and between the left and the right sides of the head (b).

Taking into account a spatial-dependent detection of specific patterns of electrical brain activity, we performed a more detailed analysis of how the separation between real and imaginary movements depends on the electrode position. The obtained results are shown in Figure 3. Following Fig. 3a, distinctions between real and imaginary hand movements become clearer when considering EEG-channels placed closer to the forehead. When the electrode position is changed in a perpendicular direction (from the left side of the head to the the right side), estimated measure do not show significant changes in the quality of pattern separation (Figure 3b).

4. CONCLUSION

In this study we analyzed specific patterns of electrical brain activity in a group of untrained subjects related to real and imaginary movements of the right hand. Our analysis was based on the Hölder exponents computed with the multifractal analysis revisited with wavelets. We have shown the ability to distinguish between real and imaginary movements based on short fragments of experimental recordings that is important for potential application of the used approach as a recognition algorithm within a BCI. We have shown that this recognition requires an appropriate selection of the EEG channel, because the quality of separation depends on the chosen position of the recording electrode.

ACKNOWLEDGMENTS

This work was supported by the grant of the President of Russian Federation for the Leading Scientific Schools of Russia (NSh-2737.2018.2) and the Russian Foundation for Basic Research (Grant No. 16-29-08221).

REFERENCES

[1] Makeig, S., Enghoff, S., Jung, T. P., and Sejnowski, T. J., "A natural basis for efficient brain–actuated control," *IEEE Trans. Rehabil. Eng.* **8**, 208–211 (2000).

[2] Sviderskaya, N. E. and Antonov A. G., "Influence of individual psychological features on the EEG spatial organization in nonverbal divergent thinking," *Human Physiology* **34**, 565–573 (2008).

[3] Maksimenko, V. A., Heukelum, S., Makarov, V. V., Kelderhuis, J., Luttjohann, A., Koronovskii, A. A., Hramov, A. E., and van Luijtelaar, G., "Absence seizure control by a brain computer interface," *Scientific Reports* **7**, 2487 (2017).

[4] Farwell, L. A. and Donchin, E., "Talking off the top of your head: toward a mental prosthesis utilizing event related brain potentials," *EEG and Clinical Neurophysiology* **70**, 510–523 (1988).

[5] Mak, J. N., Arbel, Y., Minett, J. W., McCane, L. M., Yuksel, B., Ryan, D., Thompson, D., Bianchi, L., and Erdogmus, D., "Optimizing the P300–based brain–computer interface: current status, limitations and future directions," *Journal of Neural Engineering* **8**, 025003 (2011).

[6] Hoffmann, U., Vesin, J. M., Ebrahimi, T., Diserens, K., "An efficient P300–based brain–computer interface for disabled subjects," *Journal of Neuroscience Methods* **167**, 115–125 (2008).

[7] Pires, G., Nunes, U., Castelo-Branco, M., "Comparison of a rowcolumn speller vs. a novel lateral single-character speller: Assessment of BCI for severe motor disabled patients," *Clinical Neurophysiology* **123**, 1168–1181 (2012).

[8] Kennedy, P. R. and Bakay, R. A., "Restoration of neural output from a paralyzed patient by a direct brain connection," *Neuroreport* **9**, 1707–1711 (1998).

[9] Wolpaw, J. R., "Brain-computer interfaces as new brain output pathways," *The Journal of Physiology 579*, 613–619 (2007).

[10] Kaplan, A. Y., Shishkin, S. L., Ganin, I. P., Basyul, I. A., and Zhigalov, A. Y., "Adapting the P300-based brain-computer interface for gaming: a review," *IEEE Transactions on Computational Intelligence and AI in Games* **5**, 141–149 (2013).

[11] Huang M., Wu, P., Liu, Y., Bi, L., and Chen, H., "Application and contrast in brain-computer interface between Hilbert-Huang transform and wavelet transform," In *The 9th International Conference for Young Computer Scientists, ICYCS, 18–21 November 2008* 1706–1710 (2008).

[12] Vaughan, V. M., "Brain-computer interface technology: a review of the second international meeting," *IEEE Trans. Rehabil. Eng.* **11**, 94–109 (2003).

[13] Muzy, J.-F., Bacry, E., and Arneodo, A., "Wavelets and multifractal formalism for singular signals: Application to turbulence data," *Phys. Rev. Lett.* **67**, 3515–3518 (1991).

[14] Muzy, J.-F., Bacry, E., and Arneodo, A., "The multifractal formalism revisited with wavelets," *Int. J. Bifurcation Chaos* **4**, 245–302 (1994).

[15] Pavlov, A. N., Sosnovtseva, O. V., Ziganshin, A. R., Holstein-Rathlou, N.-H., and Mosekilde E., "Multiscality in the dynamics of coupled chaotic systems," *Physica A* **316**, 233–249 (2002).

[16] Pavlov, A. N., Sosnovtseva, O. V., and Mosekilde, E., "Scaling features of multimode motions in coupled chaotic oscillators," *Chaos, Solitons and Fractals* **16**, 801–810 (2003).