Separation between real and imaginary movements from multichannel EEG signals

Daria S. Grishina, Olga N. Pavlova, Yasir Kh. Mohammad, Anastasiya E. Runnova, Alexey N. Pavlov, et al.

Daria S. Grishina, Olga N. Pavlova, Yasir Kh. Mohammad, Anastasiya E. Runnova, Alexey N. Pavlov, Alexander E. Hramov, "Separation between real and imaginary movements from multichannel EEG signals," Proc. SPIE 11067, Saratov Fall Meeting 2018: Computations and Data Analysis: from Nanoscale Tools to Brain Functions, 110670F (3 June 2019); doi: 10.1117/12.2521736

Event: International Symposium on Optics and Biophotonics VI: Saratov Fall Meeting 2018, 2018, Saratov, Russian Federation

Separation between real and imaginary movements from multichannel EEG signals

Daria S. Grishina[a], Olga N. Pavlova[b], Yasir Kh. Mohammad[c], Anastasiya E. Runnova[a], Alexey N. Pavlov[a,b] and Alexander E. Hramov[a]

[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] Tikrit University/College of Dentistry Salahudin, Tikrit Qadisiyah, University Str. PO Box 42, Tikrit, Iraq

ABSTRACT

We discuss the ability to recognize the electrical activity of the brain associated with movements by the arms/legs and with imagination of such movements. Conducting experiments with a group of untrained volunteers, we show that real and imaginary movements are clearly detected using the scaling exponent of the detrended fluctuation analysis for the majority of EEG channels (usually 28-31 out of 33). Although this ability is shown regardless of the type of movements, the case of leg movements provided a slightly higher recognition results. This conclusion is supported by numerical estimations based on two quantitative measures.

Keywords: EEG, pattern recognition, signal processing, detrended fluctuation analysis

1. INTRODUCTION

The development of brain-computer interfaces (BCIs) is the topic of intensive research in the field of neurophysiology and related sciences.[1] The first ideas related to the creation of devices that can provide actions in the surrounding world, controlled by mental intentions, were limited by the capabilities of existing processors and general knowledge about the dynamics of the brain. The main achievements in the creation of BCIs are related to the last two decades, when many non-invasive devices were proposed.[2–6] Such devices provide on-line recognition of various patterns of the multichannel electroencephalogram (EEG), which are further transformed into control commands for the hardware. Examples of the developed devices include BCI for controlling the movement of cursor on the monitor screen,[7] communication devices for fully paralyzed people,[8] etc. The recent review paper[9] summarizes the current achievements in the development of non-invasive BCIs.

An important part of every BCI is software that provides identification of mental intentions by processing multichannel EEG-data. This software should recognize patterns associated, e.g., with the imaginations of different types of movements and separate them from the background EEG. This is a very complicated problem, taking into account the high variability of the electrical brain activity, even at rest. Moreover, the operator must have experience when using BCI to generate commands that will be clearly recognized. Due to this, experimental studies with BCI are mainly carried out for trained volunteers to obtain more stable results. Nevertheless, even for untrained people, it is possible to distinguish between background EEG and patterns associated with real and imaginary movements. In resent publications,[10,11] we demonstrated the ability to provide such a separation for one type of movement (e.g., a rise of the right arm) using two data processing methods, the wavelet-based multifractal formalism[12,13] and the detrended fluctuation analysis (DFA).[14,15] Both of these approaches provided similar results, but the second approach allows to significantly decrease the computation time, which is important for on-line recognition. This is the main reason, why DFA was chosen for data processing.

Unlike previous studies, here we compare different types of movements, namely movement by the left/right arm and left/right leg. We consider the case of real movements and their imaginations aiming to identify which types of movements are easier to imagine and recognize in the further processing of data based on DFA. We will

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

Saratov Fall Meeting 2018: Computations and Data Analysis: from Nanoscale Tools to Brain Functions,
edited by Dmitry E. Postnov, Proc. of SPIE Vol. 11067, 110670F · © 2019 SPIE
CCC code: 0277-786X/19/$18 · doi: 10.1117/12.2521736

show that the differences are rather subjective and depend on the operator. Nevertheless, the leg movements are separated for more EEG channels than arm movements, and the quality of their separation is somewhat better, as confirmed by the quantitative measures.

2. MATERIALS AND METHODS

2.1 Experiments

The experiments were conducted in healthy volunteers (men and women, n=16) aged 19 to 43 years in a specially equipped laboratory. The protocol was approved by the local research ethics committee of the Yuri Gagarin State Technical University of Saratov. Multichannel EEGs were acquired using the electroencephalograph "BE Plus LTM" (EB Neuro SPA), which has registration certificate No. FSZ 2011/10629 of 20.09.2011 from the Russian Federation Federal Service of Health Care and Social Development Control. The equipment used complies with the certificates UNI EN ISO 9001/ISO 9001:2008, EN 46001 ISO 13485:2012, QSR 21 CFR Part 820 of the Federal Law. In addition to the standard 10-20 setup, we used intermediate electrodes with 33 channels for each volunteer.

The experiments included background measurements (at the beginning and at the end, each consisting of 5 minutes), and the following tasks: a slow rise of the left arm (LA) in the shoulder joint, a similar rise of the right arm (RA), a slow rise of the left leg (LL), a similar rise of the right leg (RL), as well as the imagination of these procedures (imaginary movement of LA, RA, LL and RL). Movement or imagination was performed after a sound signal, and the brain activity was recorded for 3 seconds. Each experiment included 100 records of each type of movement and its imagination, which were divided into sessions consisting of 20 repetitive movements/imaginations of each type. Each session was accompanied by a short instruction on the monitor screen.

2.2 Data analysis

The recognition algorithm used in this study is based on the detrended fluctuation analysis,[14,15] which is a fairly universal approach for the analysis of nonstationary processes[16,17] being simpler compared to wavelet-based tools.[18,19] This method performs the transition from the measured time series $x(i)$, $i = 1, \dots, N$ to the profile

$$y(k) = \sum_{i=1}^{k} \left[x(i) - \langle x \rangle\right], \qquad \langle x \rangle = \frac{1}{N}\sum_{i=1}^{N} x(i), \tag{1}$$

which is further divided into segments of length n and the linear trend $y_n(k)$ in each segment is estimated with the least squares approach. The root mean-square fluctuation $F(n)$ around this trend

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} \left[y(k) - y_n(k)\right]^2} \sim n^{\alpha} \tag{2}$$

shows a power-law dependence with the scaling exponent α, which relates to the exponents describing the decay of the correlation function or the frequency dependence of the power spectrum. A more detailed description of the algorithm is given in the studies by Peng et al.[14,15]

Comparative analysis of different types of movements with the DFA approach was based on two main quantities:

(i) the number of channels K where a significant difference was found between real and imaginary movements (Mann-Whitney test, p<0.01),

(ii) the separability value S of two types of movement, estimated as

$$S = \frac{\mid \overline{\alpha}_{Re} - \overline{\alpha}_{Im} \mid}{E_{Re} + E_{Im}}, \tag{3}$$

where $\overline{\alpha}_{Re} \pm E_{Re}$ and $\overline{\alpha}_{Im} \pm E_{Im}$ are mean values with standard errors for real and imaginary movements, respectively. Both measures, K and S, are evaluated for each type of movements: LA, LL, RA and RL.

3. RESULTS AND DISCUSSION

In an attempt to confirm the ability of DFA to recognize real and imaginary movements, we considered several examples of experimental records, for which a range of scales was established, suitable for separating these two types of movements. Figure 1 shows typical dependencies of the root mean-square fluctuations $F(n)$ in a double logarithmic plot. This Figure illustrates that $F(n)$ is a power-law dependence in accordance with the a-priori assumptions (2), and the scaling exponent (and, therefore, the slope of $\lg F$ vs. $\lg n$ differs between real and imaginary movements).

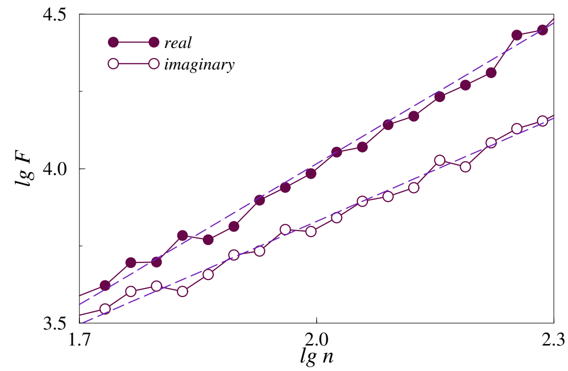

Figure 1. The dependencies of $\lg F$ vs. $\lg n$ for an example of EEG recording (the case of real and imaginary movement by the left arm).

Further, we analyzed how the separation between real and imaginary movements depends on the type of movement. For this purpose, we estimated the S measure for every channel for each volunteer. Figure 2 illustrates an example of the results obtained for an arbitrary chosen EEG record. Here we observe a reliable separation (S>1) between real and imaginary movements – for arm movements (both left and right) and for leg movements (also both left and right). This separation occurs in all channels (33 out of 33) for LA, RA and RL and for the most channels (30 out of 33) for LL.

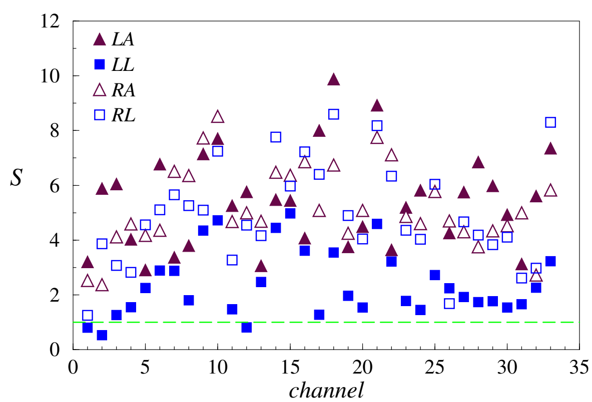

Figure 2. Estimation of S-measure for EEG-recording in one volunteer. Mean values of S in each channel are given for different types of movements.

A comparative analysis of the results for all volunteers showed that of the separation depend on the subject. Thus, for some volunteers, a better separation was reached for the left arm, for other volunteers the left leg movements provided a stronger inter-group differentiation. Regardless on the subject, all the experiments proved that real and imaginary movements can be clearly separated, and consideration of a large number of channels allows an authentic separation for most of them. Statistical analysis shows that the number of such channels usually ranges between 28 and 31, and there is a slightly better separation of leg movements (see results for LL compared to LA, and for RL compared to RA – Figure 3).

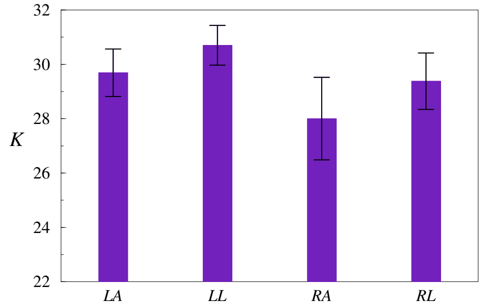

Figure 3. Results of statistical analysis of the measure K for each type of movements (averaging over all recordings for 16 volunteers).

Figure 4 confirms this conclusion for measure (3) that shows the correlation with the K-value given in Figure 3. Despite some variability of S for different subjects and repetitive experiments, the value of S strongly exceeds the level of S=1, which is associated with non-significant inter-group separation. Therefore, the recognition of imaginary movements in comparison with real movements is obvious, independently of the type of movement. According to our estimations, the consideration of leg movements may be preferable due to the larger values of both, K and S. This can be explained by the large amplitude of the arms rise, which can affect the recording equipment. However, even in this case, detection of movements is provided. Note that such a separation is observed not only between real and imaginary movements, but also between imaginary movements and the background EEG. Although the number of channels with good separation between the related EEG patterns varies, the separation is also verified for each type of movement.

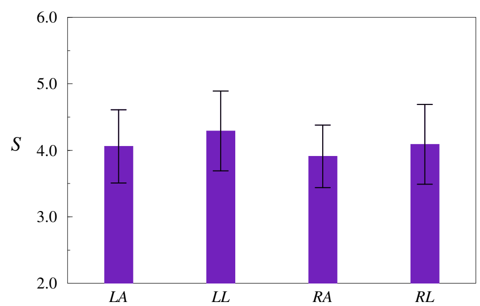

Figure 4. Results of statistical analysis of the measure S for each type of movements (averaging over all recordings for 16 volunteers).

4. CONCLUSION

We discussed the problem of separation between EEG-patterns associated with movements by the arm/leg and with their imagination. In an effort to show the recognition abilities of the detrended fluctuation analysis for this purpose, we considered a group of 16 volunteers of different ages and four types of movements (left/right arm and left/right leg). In addition to real movements, the imagination of this procedure was performed and the related multichannel EEGs were processed. We demonstrated the ability to separate between real and imaginary movements for all types of motor functions under consideration. Despite the results of the separation are subject-dependent, a reliable separation was achieved for the majority of channels (28–31 out of 33). Analysis of leg movements provided somewhat better separation results.

ACKNOWLEDGMENTS

This work has been supported by the Ministry of Science and Higher Education of the Russian Federation in the framework of the Federal Target Program "R&D for priority areas of the development of S&T complex of Russia" for the 2014–2020 (Project RFMEFI57717X0282).

REFERENCES

[1] Wolpaw, J. R. and Wolpaw, E. W., [*Brain-Computer Interfaces: Principles and Practice*], Oxford University Press, New York (2012).

[2] Stacey, W. C. and Litt, B., "Technology insight: neuroengineering and epilepsy-designing devices for seizure control," *Nature Reviews Neurology* **4**, 190–201 (2008).

[3] 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).

[4] Pires, G., Nunes, U., Castelo-Branco, M., "Comparison of a rowcolumn speller vs. a novel lateral singlecharacter speller: Assessment of BCI for severe motor disabled patients," *Clinical Neurophysiology* **123**, 1168–1182 (2012).

[5] Shih, J. J., Krusienski, D. J., and Wolpaw J. R., "Brain-computer interfaces in medicine," *Mayo Clin. Proc.* **87**, 268–279 (2012).

[6] 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).

[7] Wolpaw, J. R. and McFarland, D. J., "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *PNAS* **101**, 17849–17854 (2004).

[8] Birbaumer, N., Ghanayim, N., Hinterberger, T., Iversen, I., Kotchoubey, B., Kübler, A., Perelmouter, J., Taub, E., and Flor, H., "A spelling device for the paralysed," *Nature* **398**, 297–298 (1999).

[9] Choi, I., Rhiu, I., Lee, Y., Yun, M. H., and Nam, C. S., "A systematic review of hybrid brain-computer interfaces: Taxonomy and usability perspectives," *PLoS One* **28**, e0176674 (2017).

[10] Maksimenko, V. A., Pavlov, A. N., Runnova, A. E., Nedaivozov V., Grubov, V., Koronovskii, A. A., Pchelintseva, S. V., Pitsik, E., Pisarchik, A. N., and Hramov, A. E., "Nonlinear analysis of brain activity, associated with motor action and motor imaginary in untrained subjects," *Nonlinear Dynamics* **91**, 2803–2817 (2018).

[11] Pavlov, A. N., Runnova, A. E., Maksimenko, V. A., Pavlova, O. N., Grishina, D. S., and Hramov, A. E., "Detrended fluctuation analysis of EEG patterns associated with real and imaginary arm movements," *Physica A* **509**, 777–782 (2018).

[12] 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).

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

[14] Peng, C.-K., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., Goldberger, A. L., "Mosaic organization of DNA nucleotides," *Phys. Rev. E.* **49**, 1685–1689 (1994).

[15] Peng, C.-K., Havlin, S., Stanley H. E., Goldberger, A. L., "Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series," *Chaos* **5**, 82–87 (1995).

[16] Blesic, S., Milosevic, S., Stratimirovic, D., and Ljubisavljevic, M., "Detrended fluctuation analysis of time series of a firing fusimotor neuron," *Physica A* **268**, 275–282 (1999).

[17] Goldberger, A. L., Amaral, L. A. N., Glass, L, Hausdorff, J. M., Ivanov, P. Ch.,, Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C.-K., and Stanley, H. E., "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," *Circulation* **101**(23), e215–e220 (2000). http://circ.ahajournals.org/content/101/23/e215.full

[18] Sosnovtseva, O. V., Mosekilde, E., Pavlov, A. N., Holstein-Rathlou, N.-H., and Marsh D. J., "Double-wavelet approach to studying the modulation properties of nonstationary multimode dynamics," *Physiological Measurement* **26**, 351–362 (2005).

[19] Marsh, D. J., Sosnovtseva, O. V., Pavlov, A. N., Yip, K.-P., and Holstein-Rathlou, N.-H., "Frequency encoding in renal blood flow regulation," *American Journal of Physiology (Regul. Integr. Comp. Physiol.)* **288**, R1160–R1167 (2005).