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Neural activity during maintaining a body balance

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ABSTRACT

We have recorded multichannel EEG signals from subjects maintaining the body balance on the balance board. Having synchronized the board oscillations and the recordings we have revealed and described specific features of the cortical activity that relate to balance maintaining and reaching an equilibrium state. We have found that the increase of the equilibrium state duration is accompanied by the change of the EEG spectral amplitude in the β frequency band.

Keywords: signal analysis, body balance maintaining

1. INTRODUCTION

Ability to maintain dynamic balance and stability of the body posture plays an important role in everyday life, allowing a person to avoid injuries and save energy spent on unnecessary actions. It is known, that maintaining the vertical position of the body is a complex problem of integrated control.[1] According to the literature,[2] the cortical neuronal populations play integral roles in postural control, incorporating information from visual, somatosensory, and vestibular systems to carry out the corrective motions needed to maintain balance. For instance, the cortical structures are shown to take part in the generation of feedforward and feedback adaptive adjustments to reduce the risk of balance loss.[3–5] Moreover, according to Ref.[6] the postural control is not a fully automatic process but requires active cognitive processes originating in the cortex (e.g. sensory information processing, decision-making[7] and motor control.[8,9] The identification of the neuronal activity patterns associated with the body balance maintaining is an important task for the rehabilitation systems development.[10] These systems are aimed at restoring the motor functions due to the interaction of the patient with the robotic systems and the identified motor-related neuronal activity serves for the control commands generation. When developing such systems, the effective techniques of the neuronal activity recording and processing should be used.[11] At the same time, the developed methods are tested mostly for the neuronal activity associated with the simple movements execution.[12,13] If these methods allow to detect the neuronal activity related to the body balance control, they will be used in the human-machine systems aimed at training the human ability to maintain a body balance.

In the view of above, this work is focused on the identification of the features of the neuronal electrical activity associated with the body balance maintaining. For this reason we record the multichannel EEG signals during the maintaining body balance on the balance-board. Having analyzed the changes of the board position we have observed that the subjects are able to reach and maintain the equilibrium state for a certain time interval. The maximal length of the equilibrium state is shown to increase with increased time spent in the experiment. Finally, the enhanced ability to maintain the balance is associated with the changes of cortical activity in β-frequency band.

2. METHODS

2.1 Experimental procedure

12 healthy unpaid volunteers, 8 males and 4 females, between the ages of 20 and 43 with normal or corrected-to-normal visual acuity participated in the experiments. All of them provided informed written consent before participating. The experimental studies were performed in accordance with the Declaration of Helsinki and approved by the local research Ethics Committee of the Innopolis University.

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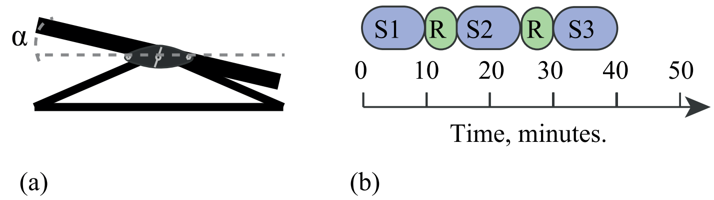

Figure 1. (a) The schematic illustration of the balance board and the definition of the angle α characterizing the board location. (b) the schematic illustration of the experimental protocol: R – resting state, S1-S3 – different sessions.

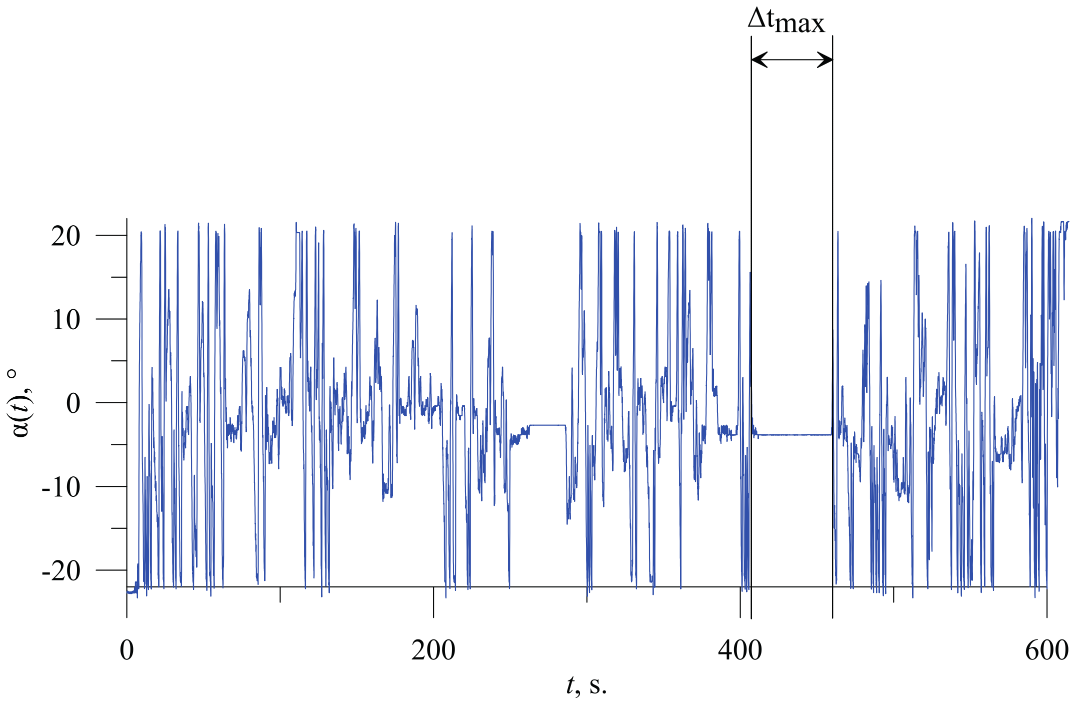

Figure 2. The change of the angle α during the experiment (based on the single subject's data).

The duration of the experiment was about 40 minutes. During the recording of signals subjects were standing on the balance platform. The angle between horizontal line and the platform elevation (as shown with the dashed line on Fig. 1, a) was registered simultaneously with the rest of the experimental data. The structure of the experiment (Fig. 1, b) included three 10-minutes sessions with two 5-minutes rest pauses between them. Registration of background (BG) activity without subject performing special instructions was carried out for 3 minutes before the balance task.

All of the subjects were instructed to maintain balanced posture during their attempts. We especially note the fact that all volunteers did not have the opportunity to train their ability to maintain balance before the experiment and, thus, the study was conducted with untrained operators. Typical form of the angle change during one of the experimental session is shown on Fig. 2. Attempt was registered if subject was able to reduce absolute value platform angle from border position to less than $\pm$ 19 °. If the duration of the attempt was longer than 1 s. then the attempt was marked as successful. The successful attempts, characterizing by the longest time interval were defined for the each session (the example of this attempt is shown in Fig. 2 as Δt_{max}).

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2.2 EEG recording and analysis

The EEG signals were recorded using the monopolar registration method and the classical extended 10–10 electrode scheme. We recorded 31 signals with two reference electrodes A1 and A2 on the earlobes and a ground electrode N just above the forehead. The signals were acquired via the cup adhesive Ag/AgCl electrodes placed on the "Tien–20" paste (Weaver and Company, Colorado, USA). Immediately before the experiments started, we performed all necessary procedures to increase skin conductivity and reduce its resistance using the abrasive "NuPrep" gel (Weaver and Company, Colorado, USA). The impedance was monitored after the electrodes were installed and measured throughout the experiments. Usually, the impedance values varied within a 2–5 kΩ interval. The electroencephalograph "Encephalan-EEG-19/26" (Medicom MTD company, Taganrog, Russian Federation) with multiple EEG channels and a two-button input device (keypad) was used for amplification and analog-to-digital conversion of the EEG signals. This device possessed the registration certificate of the Federal Service for Supervision in Health Care No. FCP 2007/00124 of 07.11.2014 and the European Certificate CE 538571 of the British Standards Institute (BSI). The raw EEG signals were filtered by a band-pass filter with cut-off points at 1 Hz (HP) and 100 Hz (LP) and by a 50-Hz notch filter by embedded a hardware-software data acquisition complex.

According to the recent works,[9,14,15] We analyzed the EEG signals power in α- and β-frequency bands, using the continuous wavelet transformation. The wavelet power spectrum $E^n(f,t) = (W^n(f,t))^2$ was calculated for each EEG channel $X_n(t)$ in the frequency range $f \in [1,30]$ Hz including both α and β ranges. Here, $W^n(f,t)$ is the complex-valued wavelet coefficients calculated as[16]

$$W^n(f,t) = \sqrt{f} \int\limits_{t-4/f}^{t+4/f} X_n(t)\psi^*(f,t)dt, \tag{1}$$

where $n = 1, ..., N$ is the EEG chanel number ($N = 31$ is the total number of chanels used for the analysis) and "*" defines the complex conjugation. The mother wavelet function $\psi(f,t)$ is the complex Morlet wavelet which is defined as

$$\psi(f,t) = \sqrt{f}\pi^{1/4}\mathrm{e}^{j\omega_0 f(t-t_0)}\mathrm{e}^{f(t-t_0)^2/2}, \tag{2}$$

where $\omega_0 = 2\pi$ is the central frequency of Morlet wavelet.

For α- and β-frequency bands the wavelet amplitudes $\bar{E}^n_\alpha(t)$, $\bar{E}^n_\beta(t)$ were calculated as

$$\bar{E}^n_{\alpha,\beta}(t) = \frac{1}{\Delta f_{\alpha,\beta}} \int\limits_{\Delta f_{\alpha,\beta}} E^n(f',t)df', \tag{3}$$

where $\Delta f_\alpha = 8 - 12\,\mathrm{Hz}$ and $\Delta f_\beta = 15 - 30\,\mathrm{Hz}$. In additional, the wavelet spectral energy was calculated for the frequency band $\Delta f_\epsilon = 1 - 30\,\mathrm{Hz}$.

$$\bar{E}^n_\epsilon(t) = \frac{1}{\Delta f_\epsilon} \int\limits_{\Delta f_\epsilon} E^n(f',t)df', \tag{4}$$

Finally, to neglect the changes of the overall EEG signal amplitude, the values (3) were normalized to the EEG spectral amplitude in the $\Delta f_\epsilon = 1 - 30\,\mathrm{Hz}$ frequency band (4):

$$E^n_{\alpha,\beta}(t) = \frac{\bar{E}^n_{\alpha,\beta}(t)}{\bar{E}^n_\epsilon(t)}. \tag{5}$$

The time-series of the wavelet power (5) were calculated for the whole time of the experimental session and then were split into the three time segments τ_1, τ_2, τ_3 associated with the maximal duration of the equilibrium state in the first, second and the third session.

For these segments the values of the wavelet spectral power were calculated for each n-th EEG channel.

$$\langle E^n_\alpha \rangle_{\tau_{1,2,3}} = \frac{1}{\tau_{1,2,3}} \int\limits_{\tau_{1,2,3}} E^n_\alpha(t')dt', \qquad \langle E^n_\beta \rangle_{\tau_{1,2,3}} = \frac{1}{\tau_{1,2,3}} \int\limits_{\tau_{1,2,3}} E^n_\beta(t')dt'. \tag{6}$$

3. RESULTS

At the first stage, the time intervals $\tau_{1,2,3}$, corresponding to the maximal duration of the equilibrium state were defined for each of three sessions (see methods). Fig. 3 illustrates the maximal duration of the equilibrium state τ (group mean $\pm$SE) for each of three sessions.

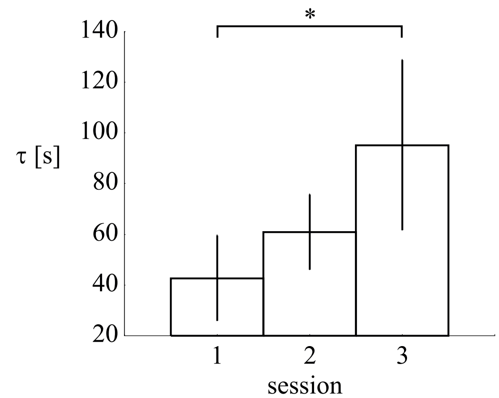

Figure 3. The maximal length of the equilibrium state. Data are shown as mean$\pm$SE, $^{*}p < 0.05$ via the Wilcoxon signed rank test

The length of these intervals was analyzed in the group of participants via a nonparametric Friedman test for three related samples. As the result a significant difference was observed for the different experimental sessions $\chi(2) = 8.167, p = 0.017$. The post hoc analysis based on the Wilcoxon signed rank test revealed the insignificant change of τ_2 when compared with τ_1 ($Z = -1.490, p = 0.136$) and insignificant change between τ_2 and τ_3 ($Z = -1.177, p = 0.239$). At the same time, the significant increase was observed for τ_3 when compared with τ_1 ($Z = -2.981, p = 0.003$). Based on the obtained results we have concluded that the maximal duration of the equilibrium state growths with the time spent in the experiment. This allows to suppose that the observed training effect can be associated with the specific features of the neuronal cortical activity.

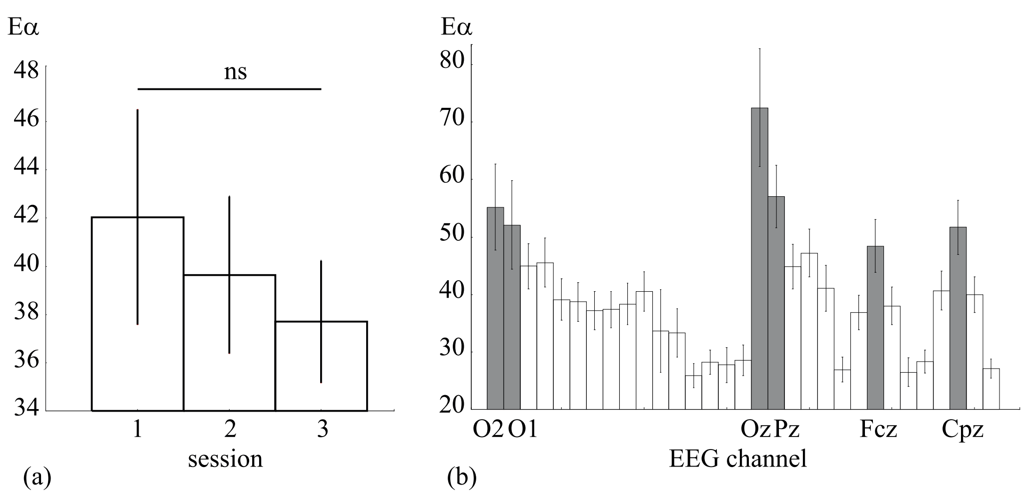

Figure 4. (a) Mean value of the α-band spectral energy during the equilibrium state for three different sessions; (b) Distribution of the the α-band spectral energy across EEG channels. Data are shown as mean$\pm$SE, $^{*}p < 0.05$ via the Wilcoxon signed rank test

To test this hypothesis we analyzed the values of wavelet energy, calculated for all EEG channels in the α and β frequency bands (see methods) using the repeated measures ANOVA. The EEG channel and the experimental session were considered as the within subject factors. For the α-band ANOVA with the Greenhouse-Geisser correction revealed insignificant change of the wavelet energy between the sessions ($F_{1.237,14.004} = 1.742, p = 0.21$) and the significant change between the different EEG channels ($F_{2.519,27.709} = 12.786, p < 0.001$). The interaction effect *EEG channel×session* was insignificant ($F_{3.965,43.610} = 1.050, p = 0.392$). Having summarized we concluded that the EEG spectral power in α-band remained the same during the experiment (Fig. 4, a) and characterized by the typical distribution across EEG channels (Fig. 4, b).

For the β-band ANOVA with the Greenhouse-Geisser correction revealed significant change of the wavelet energy between the sessions ($F_{1.252,13.775} = 5.983, p = 0.023$) and the significant change between the different EEG channels ($F_{2.185,24.03} = 10.992, p < 0.001$). The interaction effect *EEG channel×session* was insignificant ($F_{4.653,51.186} = 1.298, p = 0.281$). The post hoc analysis based on the Wilcoxon signed rank test revealed the significant increase of τ_2 when compared with τ_1 ($Z = -2.353, p = 0.019$) and insignificant change between τ_2 and τ_3 ($Z = -1.098, p = 0.272$). At the same time, the significant increase was observed for τ_3 when compared with τ_1 ($Z = -2.589, p = 0.01$). Having summarized we concluded that the overall EEG spectral power in β-band decreased during the experiment (Fig. 5 a) but characterized by the unchanged topographical properties (Fig. 5, b).

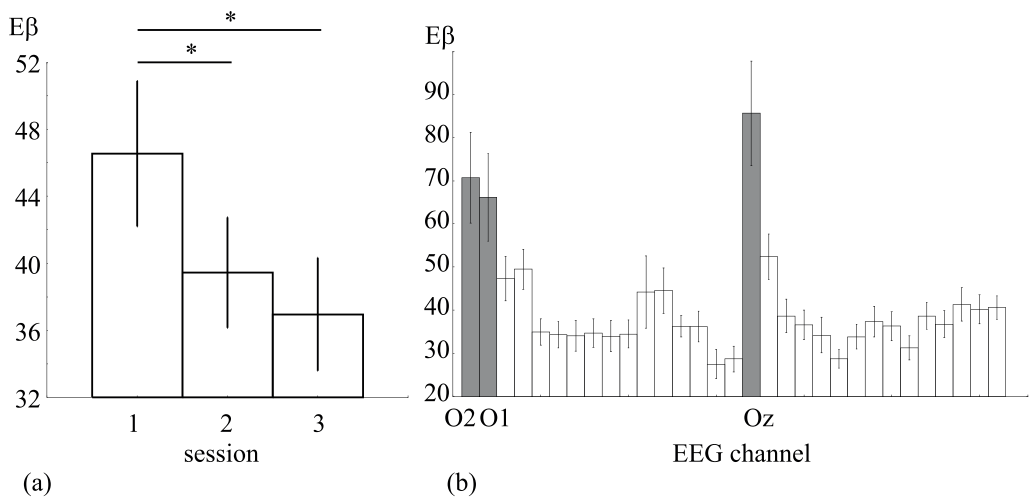

Figure 5. (a) Mean value of the β-band spectral energy during the equilibrium state for three different sessions; (b) Distribution of the the β-band spectral energy across EEG channels. Data are shown as mean±SE, $^*p < 0.05$ via the Wilcoxon signed rank test

4. CONCLUSION

The obtained results confirm that the process of the body balance maintaining is controlled by the cortical neuronal activity. Moreover, the neuronal activity in the β-frequency band can be utilized as the neurophysiological marker of the subject's ability to maintain the equilibrium state. Latter is important for the human-machine systems aimed at restoring and training the human ability to maintain dynamic balance and stability of the body posture.

5. ACKNOWLEDGMENTS

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