Report to the poster “Analysis of the muscle activation pattern during equilibrium seeking activity”

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INTRODUCTION

In modern living conditions, humans are faced with the need to solve complex motor tasks in educational, labor, everyday life and sports activities, while high demands are made on him in terms of motor training (Hayashibe et al., 2015; Dutt-Mazumder et al, 2018; Maksimenko et al, 2018; Reis et al., 2014; Melnik et al, 2017; Elices et al, 2019). The equilibrium of the human body in an upright position in the process of various motor activities seems at first glance a fairly simple function due to habituality its manifestations and natural formation from the day of birth. However, numerous studies of physiologists, clinicians, scientific researchers in the field of sports show that the equilibrium function is very complex and its value in human life is very great, and sometimes crucial (Edmunds et al. 2019; Solis-Escalante et al. 2019; Herold et al. 2019; Mierau et al. 2017; Maksimenko et al. 2017). In this work, we will try to expand the understanding of these processes with the experiment involving natural feedback for the subject performing on a balance platform. This is an important difference between this work and existing studies where subjects only passively response on the balance disturbances.

2 EXPERIMENTAL SETUP

We conducted a series of experiments involving the placement of subjects on the originally designed balance platform as shown on Fig. 1A. The difficulty of the task was regulated by a compression spring. The friction force created by the spring in the experiment was 27 N., which trained athletes found to be challenging. The number of volunteer subjects was 20 (15 male, 5 female) aged from 25 to 42 years. We instructed all volunteers before conducting the research to observe the regime of full night rest for three days.

We conducted the experimental study in the morning and afternoon periods (9 AM – 1 PM) 2 hours after a healthy meal with limited consumption caffeine and (or) other stimulating additives to food. While recording signals, subjects were standing on a balance platform.

The design of the experiment included three 10-minute sessions with two rest breaks between them. Preliminary registration of the background (BG) activity of the subject without performing special instructions was carried out for three minutes. All subjects were instructed to ensure balanced posture during their attempts. Subjects were not able to train their ability to maintain balance before the experiment, and thus we conducted the study with untrained volunteers.

This is important because some studies have shown differences in the distribution of spectral activity between trained and untrained people. For example, the amplitude of task-related power decrease in high alpha band (10–12 Hz) was lower in athletes than in the non-athletes at right frontal, left central, right central, and middle parietal areas (Del Percio, 2009; Hiroaki et al. 2018). Despite this, nevertheless, the balance of the human body is limitedly stable due to the small footprint determined by the contours of the feet and the space between them, as well as the high location of the general center of mass of the body. Therefore, even the most insignificant internal or external influences can upset the balance and bring down the body.

During the experimental session, we were recoding EEG, EMG, angle and velocity of the balance platform signals simultaneously. Such criteria as the center of gravity position were not available for the recordings. EEG channels data were recorded continuously according to the standard “10-10” configuration. As shown on the scheme of the EMG electrodes in Fig. 1B, arrangement included next muscles: Tibialis Anterior, Gastrocnemius, Rectus Femoris, Semitendinosus. 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. 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. We filtered raw EEG signals with a band-pass filter with cut-off points at 1 Hz (HP) and 100 Hz (LP) and with a 50 Hz notch filter embedded in a hardware-software data acquisition complex.

For the better understanding of how interaction between muscles could help to maintain balance, we developed a model based on mechanical principles. There are known a lot more complicated models for the lower limbs movement, but most of them involve walking activity or excessive data amount not available for our study. The scheme of the model consists of six kinematic links. The sagittal plane movement was not relevant for the balance task so we used only the coronal plane movement. The lever of the balance platform operates by applying different forces at equal distances from the fulcrum. The resulting force applied to the platform lever is proportional to the second derivative of the angular change and can be estimated as the following:

$$F_{rot}(t) = \sum_k m_k F_k(t-\tau) \cdot f(\tilde{F}_k, \phi_k(t)) - \mu mg + F_{iner}(t) + F_{passiv}(t) + m\xi_m(t)$$

Where k index denotes the body part corresponding to the muscle, m_k is the mass of the body part and F_k is the active force applied by the muscle, f — is the corresponding trigonometric function factor for the F_k and hinge angle ϕ_k, μ is a sliding friction coefficient, g — standard gravity value, F_{iner} — fictitious force of the platform, F_{passiv} — the resulting force of the difference between the weights applied to the shoulders of the platform, $\xi(t)$ — body movement noise (Gaussian noise with zero mean and 0.05 deviation).

One of the most classical equations that relates tension to velocity with regard to the internal thermodynamics is the Hill Model:

$$(v+b)(F=a)=b(F_0+a)$$

where F is the tension in the muscle, v is the velocity of contraction, F_0 is the maximum isometric tension, a — coefficient of shortening heat, b is the scaling coefficient, calculated as

$$b=av_0/F_0$$

where v_0 is the maximum velocity, when $F = 0$. One of the more advanced form of it was implemented in the Sanger model [21] and model proposed by [22]:

$$\dot{a}=\begin{cases}(x-a)[x/\tau_{act}+(1-x)/\tau_{deact}],\ x\geq a\\ (x-a)/\tau_{deact},\ x<a\end{cases}$$

$x(t)$ more closely represents the neural excitation of the muscle than the muscle active state, a is muscle activation while τ_{act} and τ_{deact} are the activation and deactivation time constants, respectively. For the muscle-tendon dynamics dynamics we adapted the tendon equation from the [22]:

$$F_T(a)=F_{T\max}\cdot\frac{\exp\left(\frac{\beta}{\lambda}\left(\frac{a-a_{\max}}{a_{\max}}\right)\right)-1}{\exp(\beta)-1}$$

Here F_{Tmax} is the maximum muscle isometric force, β is a shape factor, and λ is a reference strain. The force for each muscle is estimated in the following manner:

$$F_k=F_{T},_k\,(a(x(t-\tau_{eff})+\sum_k\tilde{x}_k+\xi_{neur}(t))+\xi_k(t),\ k=1..8.$$

Here $\xi_k(t)$ is the movement noise and $\xi_{neur}(t)$ is a neural noise, $\tilde{x}$ — interactional effect from other muscles, τ_{eff} is the efferent time delay constant [23]. The force of the flexor extensor pair for one of the hinge joint can be defined in the following form.

$$F_{FE}=(F_{flex}-F_{ex})\cos(\phi_{FE})$$

The feedback loop of the neural controllers is used in the following form:

$$y(t)=k_1\alpha(t-\tau_{eff})+k_2\omega(t-\tau_{eff})+k_3\dot{\omega}(t-\tau_{eff})+k_4\int_{-2\tau_{eff}}^{-\tau_{eff}}\alpha(\tilde{t})dt+k_5\dot{x}_{com}(t-\tau_{eff})$$

Here k_i is a feedback coefficient of the corresponding block, ω is the angular speed of the platform, x_{com} is the abscissa of the projection of the center of mass.

3 DATA ANALYSIS AND RESULTS

For the analysis of behavioral characteristics during training, we used indicators such as the duration of the longest successful attempt (L_{max}) of maintaining equilibrium, the total duration of successful sections of maintaining equilibrium (L_{Σ}):

$$L_{\Sigma} = \sum_i L_i \qquad (1)$$

Total number of attempts to maintain equilibrium (N), the percentage of successful attempts:

$$R = \frac{N\text{succ}}{N} \cdot 100\% \qquad (2)$$

Dynamics of changes between the characteristics are shown in Fig. 1E for sessions and for parts of sessions. We observe significant changes between sessions for L_{max}, N and L_{Σ}. As one can see on Fig. 1E) Most of the longest equilibrium intervals were observed in the 3rd session (15 out of 20 subjects have the longest interval in the 3rd session, four in the 2nd and one case for the 1st session). The length of these intervals was analysed in the group of participants via a nonparametric Friedman test for three related samples. L_{max} increases from session to session. As the result a significant difference was observed for the different experimental sessions $\chi(2) = 6.657$; $p = 0.007$. The post hoc analysis based on the Wilcoxon signed rank test (Wilcoxon, F., 1945) revealed the significant increase for S2 when compared with S1 ($Z = -3.424$; $p = 0.002$), for S3 when compared with S2 ($Z = -2.763$; $p = 0.006$), for S3 when compared with S1 ($Z = -3.771$; $p = 0.001$). Based on the obtained results we have concluded that the maximal duration of the equilibrium state growths with the time spent in the experiment.

The length of these intervals was analysed 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 $\chi(2) = 19.700$; $p < 0.001$. The post hoc analysis based on the Wilcoxon signed rank test revealed the significant increase for S2 when compared with S1 ($Z = -3.267$; $p = 0.001$), for S3 when compared with S2 ($Z = -2.539$; $p = 0.012$), for S3 when compared with S1 ($Z = -3.678$; $p = 0.001$).

This effect is not so surprising, as the experiment is not very easy for the untrained subjects and humans start to wear due to fatigue (Nardone et al. 1997; Chabran et al. 2002). For the dynamics inside sessions, R and L_{Σ} were the most promising. The percentage of successful attempts significantly increases during the session that demonstrates the process of successful learning during the exercise. A significant difference was observed for the different parts of sessions $\chi(2) = 3.942$; $p = 0.041$. The post hoc analysis based on the Wilcoxon signed rank test revealed the insignificant increase for the 2nd part when compared with the 1st part ($Z = -1.381$; $p = 0.166$), for the 3rd when compared with the 2nd ($Z = -0.971$; $p = 0.332$), but significant for the 3rd when compared with the 1st ($Z = -2.613$; $p = 0.009$). Total duration of successful sections of maintaining equilibrium as can be seen on Fig 3d) is constantly increasing not only from session to session, but inside sessions as well. This characteristic can be used as the steadiest for the estimation of learning efficiency. For the characteristic of total duration we calculated the repeated measures ANOVA with the Greenhouse-Geisser correction (Greenhouse, S. W., Geisser, S. 1959) revealed significant change of the value between the sessions ($F_{1.966;37.447} = 41.224$; $p < 0.001$), parts of sessions ($F_{1.571;32.062} = 12.883$; $p = 0.001$).

The interaction effect part×session was insignificant ($F_{1.628; 30.922} = 0.734$; $p = 0.462$). To observe the changes in brain activity during the experiment, we looked at the spectral density of EEG leads. Background activity demonstrated increase in the domain of low-frequency oscillations, located topologically in the frontal lobe area. These oscillations most likely connected with the intellectual activity during the anticipation of the exercise. The separate leads wavelet analysis conducted in our previous work demonstrated most apparent changes (amplitude decrease) on the O_1, O_2, O_z, P_z, C_{pz} leads. For the β-band of all EEG channels we calculated the repeated measures 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 ($F_{4.653; 51.186} = 1.298$; $p = 0.281$). Comparison of the longest equilibrium attempts in the 1st and the 3rd sessions demonstrates more focused activity in the sensorimotor area while the power spectral density shows overall decrease notable for the low beta-band frequency domain (13–29 Hz). This observation can be explained by the developed of so called “neural efficiency” proposed in some works for the explanation of the fact that neural activity is reduced in experts compared to untrained subjects.

4 CONCLUSIONS

The obtained results confirm that untrained subjects were able to develop the ability to maintain equilibrium on a balance platform. The learning involves longer and more successful but less frequent attempts. Neural activity in the sensorimotor area of the cortex shows significant changes during balance maintaining process, accompanied by overall activity decrease. We have shown that stability can be achieved even in conditions of disequilibrium with a narrow area of the support (see-saw platform) despite the individual reactions are unstable, and the information used for the position control is delayed due to the inertia. Significant changes between sessions for the longest successful attempt and increase of the total balance duration supports the idea of training strategy aimed toward better efficiency in the best attempt rather than executing more attempts. EMG analysis has shown that more effective balance keeping requires more correlated interaction between muscle groups on both legs. Analysis of the model data revealed that correlation increase should be specific rather than random to improve such complex activity as balance keeping.

This study supports the theory of the cerebral cortex involvement in maintaining posture during balance tasks.

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REFERENCES

Hayashibe, M., Guiraud, D., Pons, J., *et al.* 2015 Editorial: biosignal processing and computational methods to enhance sensory motor neuroprosthetics. *Front Syst Neurosci.* Vol. 9, pp. 434.

Dutt-Mazumder, A., Dhar, S., Dutt-Mazumder, C., 2018 Postural Stability Variables for Dynamic Equilibrium, *Journal of Nature and Science*. Vol. 4(12), e541.

Maksimenko, V. A., Pavlov, A. N., Runnova, A. E., *et al.* 2018. Nonlinear analysis of brain activity, associated with motor action and motor imaginary in untrained subjects. *Nonlinear Dynamics.* Vol. 91(4) pp. 2803.

Reis, P., Hebenstreit, F., Gabsteiger, F., *et al.*, 2014. Methodological aspects of EEG and body dynamics measurements during motion. *Frontiers in Human Neuroscience.* Vol. 8, pp. 156.

Melnik, A., Hairston, W., Ferris, D., König, P., 2017. EEG correlates of sensorimotor processing: independent components involved in sensory and motor processing. *Scientific Reports.* Vol. 7, pp. 4461.

Elices, I., Levi, R., Arroyo, D. *et al.* 2019. Robust dynamical invariants in sequential neural activity. *Scientific Reports.* Vol. 9**,** pp. 9048.

Pitsik, E. N., Frolov, N. S., Kraemer, *et al.*, 2020. Motor execution reduces EEG signals complexity: Recurrence quantification analysis study. *Chaos.* Vol. 30(2), 023111.

Edmunds, K., Petersen, H., Hassan, M., *et al.* 2019. Cortical recruitment and functional dynamics in postural control adaptation and habituation during vibratory proprioceptive stimulation, *Journal of Neural Engineering*. Vol. 16(2), pp. 026037.

Solis-Escalante, T., van der Cruijsen, J., de Kam, D., *et al.* 2019. Cortical dynamics during preparation and execution of reactive balance responses with distinct postural demands. *Neuroimage*. Vol. 188, pp. 557–571.

Herold, F., Törpel, A., Schega, L., *et al.*, 2019. Functional and/or structural brain changes in response to resistance exercises and resistance training lead to cognitive improvements — a systematic review. *Eur Rev Aging Phys Act.* Vol. 16**,** art. 10.

Mierau, A., Pester, B., Hülsdunker, T., *et al.* 2017. Cortical correlates of human balance control. *Brain Topography*. Vol. 30(4), pp. 434–446.

Maksimenko, V. A., Luttjohann, A., Makarov, V. V., *et al.* 2017. Macroscopic and microscopic spectral properties of brain networks during local and global synchronization. *Phys Rev E*. Vol. 96(1), pp. 012316.

Del Percio, C., Babiloni, C., Marzano, N., *et al.*, 2009. “Neural efficiency” of athletes brain for upright standing: a high-resolution EEG study, *Brain Research Bulletin*. Vol. 79(3–4), pp. 193–200.

Hiroaki, M., Takahiro, H., Yuya, M., Foti, D., Hajcak, G., 2018. Feedback Related Electroencephalogram Oscillations of Athletes With High and Low Sports Anxiety. *Frontiers in Psychology*. Vol. 9, pp. 1420.

Wilcoxon, F., 1945. Individual comparisons by ranking methods. *Biometrics Bulletin*. Vol. 1(6), pp 80–83.