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Mathematical model and dynamical analysis of the human equilibrium seeking training

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Abstract. The *purpose* of this work is to determine the ability of the partial directed coherence method to identify the directed interaction between nonlinear systems correctly in presence of nonlinear couplings between systems, as well as in the case when the measured signals are generated by objects of high dimension. The another purpose is to determine the dependence of the coupling estimation results on the parameters: series length, sampling rate, model dimension and the coupling architecture. *Methods*. In this paper, the possibilities and limitations of the frequency-resolved approach (partial directed coherence) to describe the couplings between high-dimensional time series are investigated. Surrogate time series constructed by permutation of realization are used to determine the significance of the results. *Results*. Coupling architecture in ensembles of small-dimensional oscillators can be correctly identified for linear and nonlinear systems connected in case of both linear and nonlinear coupling. For complex composite signals, when each measured time series is the sum of the signals of many individual oscillators, the technique is not specific enough, revealing non-existent connections, and it is not sensitive enough, missing the existing ones. *Conclusion*. The criteria for applying the partial directed coherence method to different signals are formulated. The measure does not show indirect couplings at sufficient series length, sampling rate and model dimension in contrast to the pairwise methods of Granger causality and transfer entropy. The measure works well for noisy time series. The method allows to study the connectivity in an ensemble of an arbitrary number of oscillators. The method allows to determine at what frequencies the interaction occurs. The partial directed coherence method gives acceptable results for series of length 80 and more characteristic periods in comparison with the Granger causality method, for which the efficiency is declared already at 4–16 characteristic periods.

Keywords: partical directed coherence, coupling, nonlinearity, nonlinear systems, nonlinear coupling, high–dimensional system.

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Математическая модель и динамический анализ тренировки удержания равновесия

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Аннотация. *Цель* настоящего исследования – определить набор выигрышных для удержания равновесия комбинаций взаимодействующих мышц ног на основе анализа данных математической модели балансировочной платформы. *Методы*. В данной работе используется разработанная математическая модель балансировочной платформы, базирующаяся на механических принципах. Для статистического анализа связей между временными рядами рассчитываются корреляции Пирсона, а для статистического анализа данных – метод дисперсионного анализа (ANOVA) и постфакторный анализ. *Результаты*. Предложена математическая модель балансировочной платформы. Получены распределения коррелированных пар мышц для модели балансировочной платформы. В результате использования численного моделирования определены границы нахождения возможного паттерна активации мышц, который будет положительно повлиять на удержание равновесия. С помощью сравнительного анализа экспериментальных и модельных данных подтверждено наличие экспериментальной комбинации взаимодействующих мышц в наборе выигрышных комбинаций. *Заключение*. Полученные результаты подтверждают, что, как модель, так и нетренированные испытуемые смогли развить способность поддерживать равновесие на балансирующей платформе. Продолжительность самой длинной успешной попытки удержания равновесия значительно меняется от сессии к сессии. Испытуемые были более успешны, чем модель, и продемонстрировали более длительные попытки удержания равновесия во время экспериментальных сессий. Анализ данных модели показал, что увеличение коррелированного взаимодействия должно быть специфическим, а не случайным, чтобы положительно влиять на поддержание равновесия. Также было показано, что неограниченное увеличение корреляции даже между потенциально выигрышными парами мышц не приведет к более длительному удержанию равновесия.

Ключевые слова: балансировочная платформа, связанность, моделирование, корреляция, тренировка, равновесие.

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Introduction

In everyday life, a person is faced with the need to solve complex motor tasks in education, work, and sports [1–7]. The balance of the human body in an upright position in the process of various motor actions seems at first glance to be a rather simple function. However, numerous studies of physiologists, clinicians, scientific researchers show that the balance function is very complex, which emphasizes the importance and value of balance in human life [8–12].

Currently, many works are devoted to the study of balance keeping models [13–18], as well as the features of lower limbs functioning while standing, have been conducted [19–21]. Thus, the study of the complex nonlinear dynamics of various models of maintaining balance is an urgent task at the present time. However, before the proposed model can be applied to a real system, it is necessary to define and investigate the desired characteristics of this model. The main focus of the experimental works involving real humans is pointed to the evaluation of the response to the disturbance given from the outside [21–26].

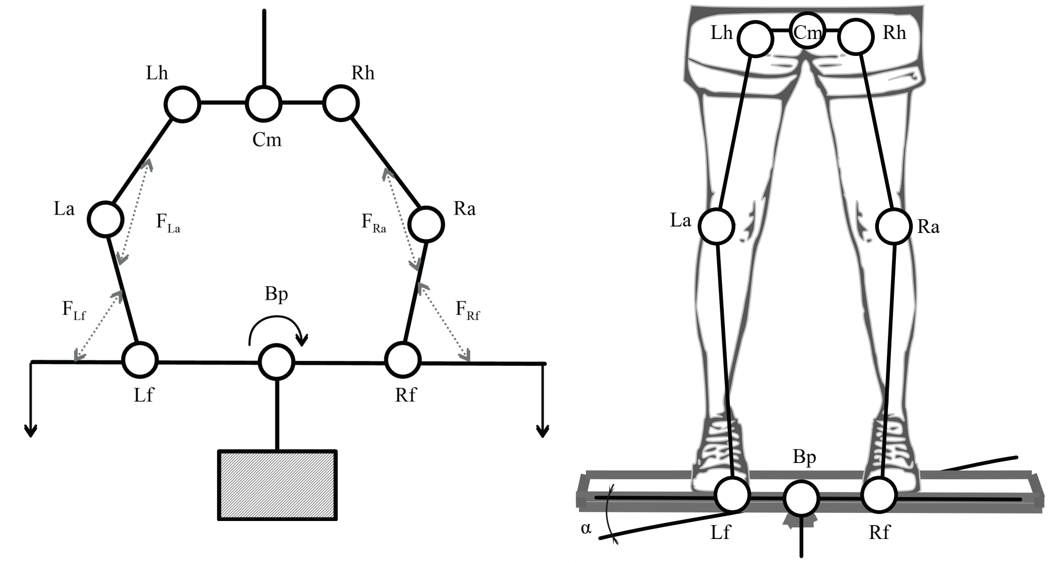
But the problem of a clear understanding of the control strategies and control mechanisms that are used by the central nervous system to sustainably stabilize an unstable posture while maintaining flexibility still remains unresolved. On the one hand, the problem of control becomes easier if we assume passive stiffness of the ankle joint and hip. However, significant passive rigidity, supplemented by active feedback moments, can lead to noticeably rigid stability, which contradicts the pliable nature of the vertical position [15]. Since there is significant recruitment of the hip and ankle muscles in the tasks requiring postural control [27], our idea was to determine the set of interacting muscles involved in balance keeping and investigate the changes in their interaction during the learning process. Experiments with a Human–Computer interface showed that subjects acquired a smart and energetically efficient strategy, in which two muscles were inactivated simultaneously [28]. However, the experiments with real movements require more interactions between muscles [29–32]. The electromyogram (EMG) coherence analysis and multiple regression analysis [33] suggest it should involve 3–4 muscle pairs into one synergy [34]. The results of the work [35] highlight the capacity of the postural control system to use asymmetrical patterns to achieve acceptable postural stability. The goal of this study is the revealing of the learning process and modelling some of the learning features observed during the experiment involving equilibrium maintaining. The learning process requires improving the interaction between muscles during long-term complex activities. To broaden our understanding of these processes, we developed a mathematical model of the balance platform and conducted a free feedback experiment for the subject maintaining balance on the platform. This is an important difference between current work and most studies in which the balance was artificially disturbed without considering the subject's actions. Separately, we note that another difference of our approach from previous works is the consideration of long-term continuous interaction, rather than a series of short repetitive similar actions.

1. The mathematical model

To better understand how the interaction between muscles is organized to maintain balance and what kind of activation pattern can form during training activities, we propose a model based on mechanical principles. Much more complex models of lower limb movement are known, but most of them involve central pattern generators or abundant data amount [16, 36–38]. The scheme of the model consists of joints, links and muscle forces as shown in Fig. 1. Movement in the sagittal plane was irrelevant to the problem of balance, so we used only movement projected onto the coronal plane. The lever of the balance platform operates by applying different forces at equal distances from the fulcrum (Bp). The force applied to the platform lever involves active muscular pressure [39] besides friction, fictitious force and weight in usual lever scales. The resulting force can be obtained through the momentum proportional to the second derivative of the angular change estimated as the following:

$$F_{\text{res}}(t) = \sum_k m_j F_j(t-\tau) f(\tilde{F}_j, \phi_j(t)) - (\Delta m_{\text{LR}}(t) + \eta(t))g + F_{\text{iner}}(t) + F_{\text{frict}}(t) \quad (1)$$

where m_j is the mass of the link (is equal usually 5–6 kg for the young adult) and F_j is the force applied by the muscle pair, f – is the corresponding trigonometric function factor for the F_k and joint angle ϕ_k, k index denotes the link of the scheme corresponding to the muscle, F_{frict} is a sliding friction force (set as 25 N to match the experiment), g – standard gravity value, F_{iner} – fictitious force of the platform, $\Delta m_{\text{LR}}(t)$ – the resulting difference between the weights applied to the shoulders of the platform, τ – delay in the feedback loop, $\eta(t)$ – movement disturbance [40] (standard deviation value was chosen equal to 0.01 from [41]). The inert model blocks shown in the Fig. 1 are the beam between the left and right feet and pelvis between the hips, incorporating the center of mass Cm. Active model blocks include thigh and shin blocks for the right and left legs accordingly. Muscle pair forces F_j correspond to the flexor and extensor forces applied to the bones attached to the corresponding joint. We looked at



a *b*

Fig. 1. The kinematic link scheme of the balance platform model with a human lower limbs (Right and left side joints: articulatio coxae, articulatio genus, articulatio talocruralis and Cm – center of mass); *b* – the corresponding experimental scheme. α denotes the platform angle

well-researched classical studies to model muscle activation. One of the most classical equations that relates tension to velocity with regard to the internal thermodynamics is the Hill Model [42]:

$$(v + b)(F + c) = b(F_0 + c), \tag{2}$$

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

$$b = \frac{cv_0}{F_0}, \tag{3}$$

where v_0 is the maximum velocity, when $F = 0$. Hill's equation describes the relationship between the tension and the contraction in the muscle. Therefore, the higher the load applied to the muscle, the lower the contraction velocity. One of the more advanced form of it was implemented in the Sanger model [43]. To obtain an activation estimate, for the muscle-tendon dynamics we adapted the tendon equation from [14]:

$$F(h) = F_{I\,\max} \frac{\exp\left(\gamma/\beta\left(h\right)\right) - 1}{\exp(\gamma) - 1} \tag{4}$$

here $F_{I\,\max}$ is the maximum muscle isometric force, γ is a shape factor, and β is a reference strain. Combining muscle activations from Eq. (4), muscle interaction effects and noise influence, we can estimate the force for each muscle is estimated in the following manner, h is the neural signal. Muscle parameters for the shape factor, muscle activation time constants (49–68 ms), muscle activation time constants (62–76 ms), and maximum isometric force values (2–5) were taken from the [14]. Both left and right halves of the model are identical. Considering that, we can state it is doesn't have a dominant leg and regard the mirrored situations as equal within themselves. The equation for flexor-extensor pair attached to the each of the joints depicted in the Fig. 1 as Lh (Left hip), La (Left ancle), Lf (Left foot), Rh (Right hip), Ra (Right ancle), and Rf (Right foot), is considered as following:

$$\begin{aligned} F_{\mathrm{FE}} = F_{\mathrm{flex}}(h(y(t-\tau_e) + \sum_k \tilde{x}_k - F_{\mathrm{ext}}(h(y(t-\tau_e) + \\ + \sum_k \tilde{x}_k + \varepsilon(t)) + \eta_{\mathrm{FE}}(t))|\cos(\varphi_{\mathrm{FE}})|. \end{aligned} \tag{5}$$

here k denotes the index corresponding to one of the four flexor-extensor pairs, the $\eta_k(t)$ is the sporadic muscle activity and $\varepsilon(t)$ is a neural noise modelled with the weak Gaussian noise (zero mean, standard deviation 0.05 [44]), $\tilde{y}$ – interaction influence from other muscles, τ_e is the efferent time delay constant (80 ms) [45] (the time required to transmit neural impulses from the brain to the muscles), φ_{FE} denotes the angle between forces induced by flexor and extensor muscles. These forces can be applied to the Eq. (1). The feedback loop of the neural controllers should include the changes in platform angle, velocity and acceleration [46] with respect on efferent delay times [45] as well as the integral perception of the platform movement and center of mass displacement [47, 48]. In the normal upright position, this assessment is mainly determined by proprioceptive signals from the ankle joint, ankle muscles and the foot. Slight wobble prevents accurate estimation of such parameters [49]. The resulting feedback signal is used in the following form:

$$x(t) = p\alpha(t-\tau_e) + \frac{1}{8}(\omega(t-\tau_e) + \frac{1}{2}\dot{\omega}(t-\tau_e) + \int\limits_{-2\tau_e}^{-\tau_e} \alpha(t)dt) + \frac{2}{5}\dot{y}_c(t-\tau_e). \tag{6}$$

Here p is a feedback coefficient for the angle value, ω is the angular speed of the platform, $\alpha(t)$ is the balance platform angle, y_c is the coordinate of the center of mass projection. For generation the neural signals $y(t)$ in Eq. (5) we used a model reference neural network controller [50] where desired reference input signal was a weak Gaussian noise as one the possible variants [51] and the reaction input is $z(t)$ to compensate for inclination. The model was developed in Simulink IDE and solved using the Euler–Heun method [52]. Both right and left parts of the model are identical. It is effectively means that the model doesn't have a lead foot and mirrored situations can be seen as equal.

2. Results

We used numerical simulations to find a possible muscle activation pattern that can positively affect equilibrium maintaining. Equilibrium attempts were determined as the time between consecutive moments when platform angle stayed withing the $\pm 19°$ limits. Attempt was count as successful if its duration was longer than one second. We used such indicators criteria as the duration of the longest successful attempt ($L_{\max}$) of maintaining equilibrium, the percentage of successful attempts, and the total duration of successful attempts of maintaining equilibrium (L_{Σ}). We took all possible combinations of muscles, with the exception of the mirror ones, and sequentially increased the correlation coefficients between the selected 3 or 4 pairs of muscles. Out of 16460 combinations only 2029 lead to positive addition of equilibrium time within the experiment and 139 combinations ($< 1\%$) gave the addition equal or more than 10 s. Probability distributions of increase or decrease in equilibrium time increment for the model data is presented in the Fig. 2, *a*, *b*, that shows that interaction should be specific in order to improve such complex activity as balance keeping. A large portion of the distribution lies in negative range, what shows that increased interaction between most muscled doesn't help with balance keeping. So, the model gave us prediction of rather limited set of interaction patterns for the successful balance keeping.

These changes describe the process of training subjects during the balance keeping. It is known that complex actions require strong interaction between muscles [53], but strong interaction between all muscles is inefficient and energy costly, so the living system require a strategy to use the limited amount of interactions to solve the task [30]. If neural synchrony is the mechanism involved in muscle formation, we would expect a certain pattern of interaction between muscles that needs to be coordinated to maintain a balanced posture [32].

The correlation structure in each of the muscles of interest was presented by symmetric matrix sized 8×8, although only 28 coefficients of the upper-corner are unique, and the part below including the

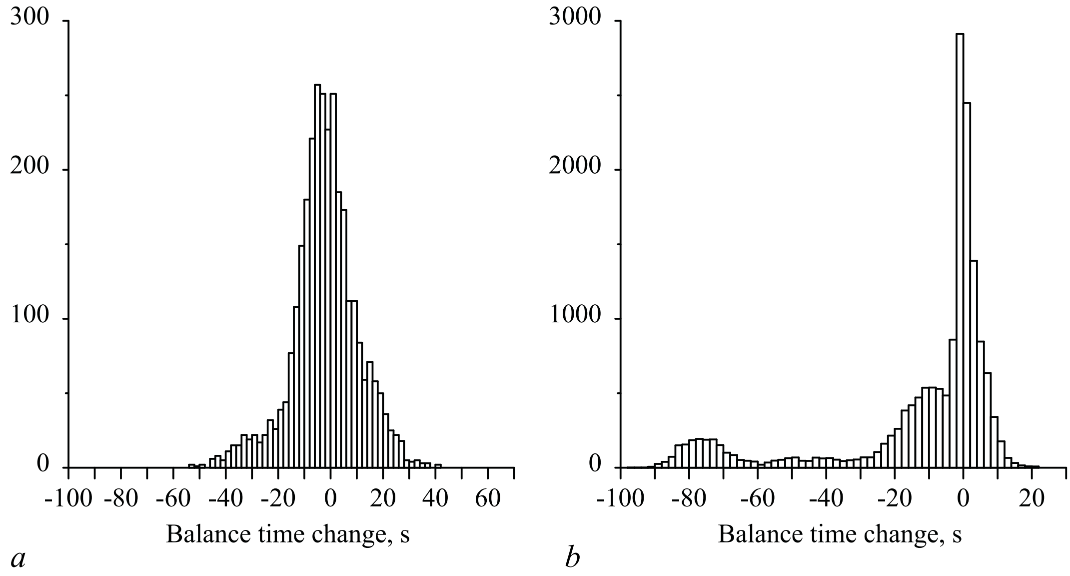


Fig. 2. The probability distribution of the simulation balance time change between all possible correlated muscle combinations in the model for 3 muscle pairs (*a*), 4 muscle pairs (*b*)

main diagonal can be left out as mirrored duplicates. For each of twenty participants we calculated ten correlation matrices for all experimental sessions. Then, we calculated correlation matrices, averaged over 10 trials, in each experimental session. Statistical analysis showed that out of 28 possible combinations of correlation coefficients only four have a significant positive addition: left Gastrocnemius – right Tibialis (LGM–RTA), left Gastrocnemius – right Gastrocnemius (LGM–RGM), right Gastrocnemius – right Tibialis (RGM–RTA), right Rectus Femoris – right Tibialis (RRF–RTA). This combination is somewhat consistent to the results shown by others [32]. All of the coefficients increase from session to session, but more apparent changes are shown between the first and the second session, as the total duration of the equilibrium for subjects.

3. Discussion

Experimental validation of the obtained results was conducted on a group of 20 (15 male, 5 female) healthy subjects, range: 25 to 42 years. Subjects had no history of musculoskeletal pathology, neurodegenerative or infectious disease, chronic ankle instability, recent ankle sprain, vestibular pathology and visual impairment. The experimental study was performed in accordance with the Declaration of Helsinki. All participants gave their written informed consent prior to the onset of the study. To analyze muscle correlation we calculated Pearson correlation coefficient between the EMG channels. For two data samples (two EMG channels in this case) of same length this coefficient can be calculated as proposed in [54]. For the average correlation coefficients, we carried out within the session repeated measures ANOVA analysis. The post hoc analysis based on the Wilcoxon signed rank test [55] showed significant changes between sessions for the longest successful attempt and the total duration of successful attempts while mean duration of attempt was not significant. The length of the longest successful attempt increases from session to session. The longest balance keeping intervals were observed in the S3 – 3rd session (75% of subjects have the longest interval S3). The post hoc analysis revealed the significant increase for S2 when compared with S1 ($p = 0.002$), for S3 when compared with S2 ($p = 0.006$), for S3 when compared with S1 ($p = 0.001$).

To compare model and experimental performance, we used the obtained coefficients to increase the interaction effect between muscles in the model applying the coefficients for the connections between neural outputs and muscles in Eq. (5). We applied the coefficients sequentially for each session and used the same calculation procedure for the obtained angular data as for the experimental data to obtain the total duration of successful attempts. The results demonstrated an upward trend for both people and models, despite the fact that people are better at keeping balance in general. This combination of four muscles that have significant correlation between their EMG signals is one of the combinations from the 0.5-top percentile from the numerical simulation with the model (Fig. 2, *b*). The distribution of the correlated muscle pairs for the top 0.5-percentile of the platform (Fig. 3, *a*) suggests that the interaction between GM and TA on different legs makes the maximum contribution to the process of balance keeping while other connections are auxiliary. The difference between relatively big amount of combinations leading to the better total balance time in the numerical simulation in comparison with the single one chosen by living systems in the experiment can be explained by the relatively simple model structure and disregard to the movements in 3-dimensional space. Some of the the "better" muscle pair combinations cannot be used effectively by humans due to the simultaneous task of keeping balance in the 3-dimentional space.

There was a 1.23 times increase in the total successful attempt duration in the experiment (450.11 versus 363.86), while increase for the model was 1.07 times (202.04 versus 188.01). To find the optimal combination of the interaction effect parameters $\tilde{y}_k$ in the Eq. (5) between four aforementioned muscle connections we calculated all of the Pearson correlation coefficients for all EMG channels combinations during the first five minutes of the experiment. These coefficients were then applied to the model in order to achieve the model state equal to the untrained subject. All of the interaction coefficients besides tested pairs were fixed. Starting from that point we scanned the values of four coefficients

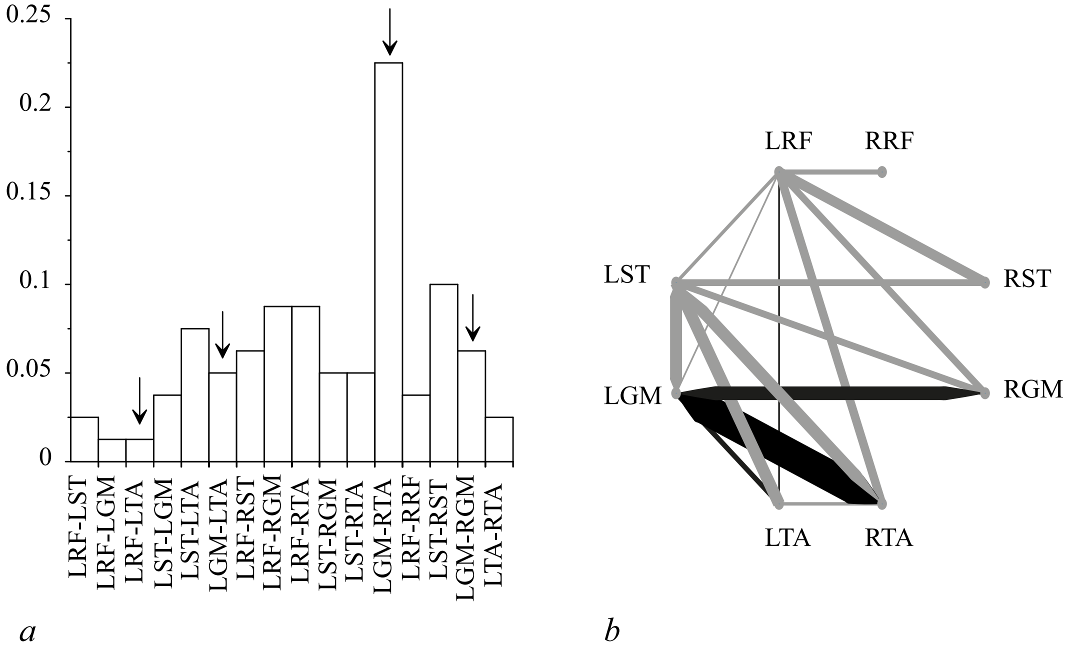


Fig. 3. *a* – The distribution of the correlated muscle pairs for the top 0.5-percentile of the platform model simulation balance time increment among the all possible combinations. Four connections that have correlation coefficients significantly increased during the experiment with live humans are marked with arrows. *b* – Connections graph of muscle pairs corresponding to 0.5-percentile in terms of the time of holding the balance by the model. Here, the width of the lines indicates how many times a muscle pair occurred among the combinations (out of 0.5-percentile), and the black color indicates the muscle pairs for which a significant increase in correlation was observed in the experiment with the subjects

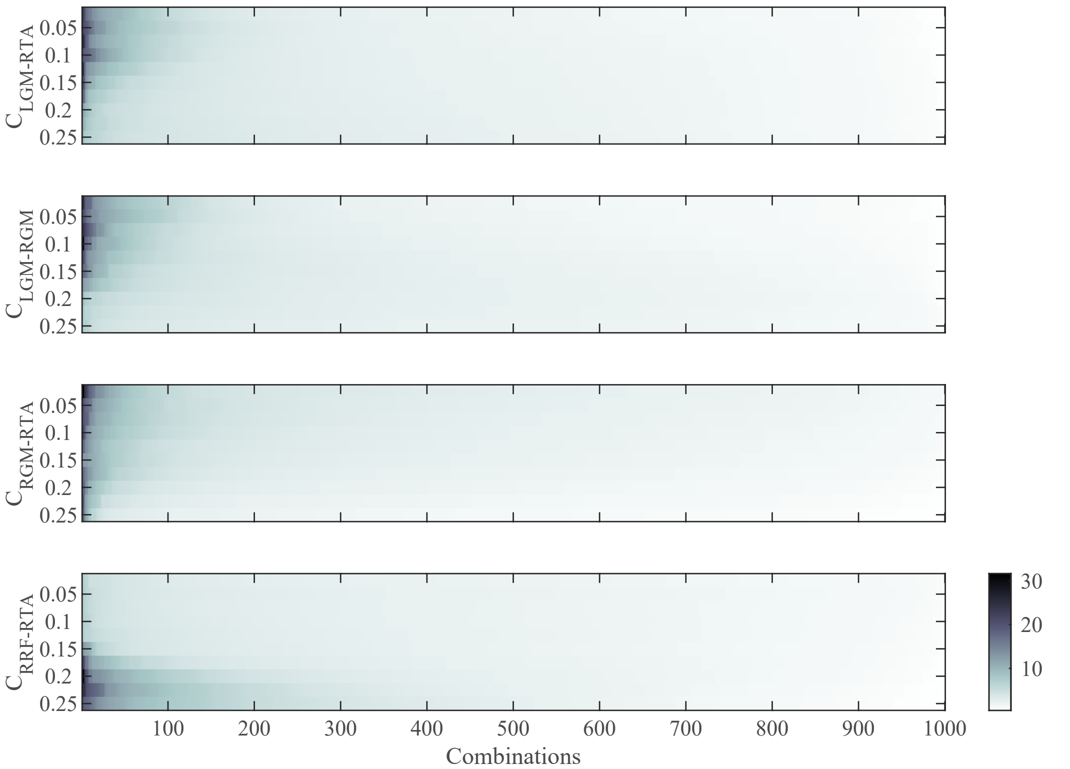


Fig. 4. The increment in total time of equilibrium duration for the platform model depending on four correlation coefficients of their respective muscle pairs, right scale shows the time in seconds

($C_{\mathrm{LGM-RTA}}$, $C_{\mathrm{LGM-RGM}}$, $C_{\mathrm{RGM-RTA}}$, $C_{\mathrm{RRF-RTA}}$) in range 0–0.5 (typical correlation coefficient range for the experimental data) and calculated the longest total time of successful attempts for the platform. The results are shown in the Fig. 4. The largest value of 308.27 seconds was obtained for the $C_{\mathrm{LGM-RTA}}$ =0.48, $C_{\mathrm{LGM-RG}}$ = 0.42, $C_{\mathrm{RGM-RTA}}$ = 0.37, $C_{\mathrm{RRF-RTA}}$ = 0.48 combination. We found that the maximums of duration values for the muscle pairs are not located in the marginal points. That means unlimited increment of correlation even between good pairs will not lead to the longer equilibrium duration time. These correlation coefficients are also differ from the values obtained for the experiment, but the ratio of these coefficients is close. Thus, we can speculate that humans with the values of correlation coefficients to the obtained in the numerical simulation could be more successful in the balance keeping experiment.

Conclusions

The regularities of the process of training to maintain equilibrium were investigated both from the point of view of behavioral characteristics and from the point of view of muscle activity. A model for maintaining equilibrium was constructed, demonstrating results qualitatively similar to those observed in the experiment. This model helped to reveal the features of the interaction between the main muscle groups in the process of maintaining equilibrium, as well as changes in their interaction during training. The obtained results confirm that both model and untrained subjects were able to develop the ability to maintain equilibrium on a balance platform. The duration of the longest successful attempt changes significantly from session to session. Participants were more successful than the model and showed better balance during the experimental sessions. Model data analysis revealed that correlated interaction increase should be specific rather than random in order to improve such complex activity as balance keeping. It also showed that unlimited increment of correlation even between good pairs will not lead to the longer equilibrium duration time. The correlations between muscle pairs have rather narrow range of values helping to achieve better duration of balance keeping and suggest a consolidtate optimal configuration including both the muscle pattern and the pattern of correlations between the muscles.

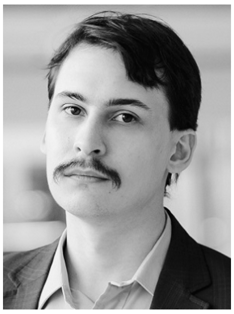
References

1. Hayashibe M, Guiraud D, Pons JL, Farina D. Biosignal Processing and Computational Methods to Enhance Sensory Motor Neuroprosthetics. Frontiers Media SA; 2016. 434 p. DOI: 10.3389/fnins.2015.00434.
2. Dutt-Mazumder A, Dhar S, Dutt-Mazumder C. Postural stability variables for dynamic equilibrium. Journal of Nature and Science. 2018;4(12):e451.
3. Elices I, Levi R, Arroyo D, Rodriguez FB, Varona P. Robust dynamical invariants in sequential neural activity. Scientific Reports. 2019;9(1):9048. DOI: 10.1038/s41598-019-44953-2.
4. Maksimenko VA, Pavlov A, Runnova AE, Nedaivozov V, Grubov V, Koronovskii A, Pchelintseva SV, Pitsik E, Pisarchik AN, Hramov AE. Nonlinear analysis of brain activity, associated with motor action and motor imaginary in untrained subjects. Nonlinear Dynamics. 2018;91(4):2803–2817. DOI: 10.1007/s11071-018-4047-y.
5. Melnik A, Hairston WD, Ferris DP, König P. EEG correlates of sensorimotor processing: Independent components involved in sensory and motor processing. Scientific Reports. 2017;7(1): 4461. DOI: 10.1038/s41598-017-04757-8.
6. Pitsik E, Frolov N, Kraemer KH, Grubov V, Maksimenko V, Kurths J, Hramov A. Motor execution reduces EEG signals complexity: Recurrence quantification analysis study. Chaos. 2020;30(2):023111. DOI: 10.1063/1.5136246.
7. Reis PMR, Hebenstreit F, Gabsteiger F, von Tscharner V, Lochmann M. Methodological aspects of EEG and body dynamics measurements during motion. Frontiers in Human Neuroscience. 2014;8:156. DOI: 10.3389/fnhum.2014.00156.
8. Edmunds KJ, Petersen H, Hassan M, Yassine S, Olivieri A, Barollo F, Friđriksdóttir R, Edmunds P, Gíslason MK, Fratini A. Cortical recruitment and functional dynamics in postural control adaptation and habituation during vibratory proprioceptive stimulation. Journal of Neural Engineering. 2019;16(2):026037. DOI: 10.1088/1741-2552/ab0678.
9. Herold F, Törpel A, Schega L, Müller NG. Functional and/or structural brain changes in response to resistance exercises and resistance training lead to cognitive improvements – a systematic review. European Review of Aging and Physical Activity. 2019;16:10. DOI: 10.1186/s11556-019-0217-2.
10. Maksimenko VA, Lüttjohann A, Makarov VV, Goremyko MV, Koronovskii AA, Nedaivozov V, Runnova AE, van Luijtelaar G, Hramov AE, Boccaletti S. Macroscopic and microscopic spectral properties of brain networks during local and global synchronization. Physical Review E. 2017;96(1):012316. DOI: 10.1103/PhysRevE.96.012316.
11. Mierau A, Pester B, Hülsdünker T, Schiecke K, Strüder HK, Witte H. Cortical correlates of human balance control. Brain Topography. 2017;30(4):434–446. DOI: 10.1007/s10548-017-0567-x.
12. Solis-Escalante T, van der Cruijsen J, de Kam D, van Kordelaar J, Weerdesteyn V, Schouten AC. Cortical dynamics during preparation and execution of reactive balance responses with distinct postural demands. Neuroimage. 2019;188:557–571. DOI: 10.1016/j.neuroimage.2018.12.045.
13. Li Y, Levine WS, Loeb GE. A two-joint human posture control model with realistic neural delays. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2012;20(5):738–748. DOI: 10.1109/TNSRE.2012.2199333.
14. Markowitz J, Herr H. Human leg model predicts muscle forces, states, and energetics during walking. PLoS Computational Biology. 2016;12(5):e1004912. DOI: 10.1371/journal.pcbi.1004912.

15. Suzuki Y, Nomura T, Casadio M, Morasso P. Intermittent control with ankle, hip, and mixed strategies during quiet standing: A theoretical proposal based on a double inverted pendulum model. Journal of Theoretical Biology. 2012;310:55–79. DOI: 10.1016/j.jtbi.2012.06.019.
16. Al-Dirini RMA, Reed MP, Hu J, Thewlis D. Development and validation of a high anatomical fidelity FE model for the buttock and thigh of a seated individual. Annals of Biomedical Engineering. 2016;44(9):2805–2816. DOI: 10.1007/s10439-016-1560-3.
17. Der R, Martius G. Self-organized behavior generation for musculoskeletal robots. Frontiers in Neurorobotics. 2017;11:8. DOI: 10.3389/fnbot.2017.00008.
18. Yao S, Zhuang Y, Li Z, Song R. Adaptive admittance control for an ankle exoskeleton using an EMG-driven musculoskeletal model. Frontiers in Neurorobotics. 2018;12:16. DOI: 10.3389/fnbot.2018.00016.
19. Loram ID, Maganaris CN, Lakie M. Paradoxical muscle movement in human standing. The Journal of Physiology. 2004;556(3):683–689. DOI: 10.1113/jphysiol.2004.062398.
20. Winter DA, Patla AE, Prince F, Ishac M, Gielo-Perczak K. Stiffness control of balance in quiet standing. Journal of Neurophysiology. 1998;80(3):1211–1221. DOI: 10.1152/jn.1998.80.3.1211.
21. Luu BL, Inglis JT, Huryn TP, Van der Loos HFM, Croft EA, Blouin LS. Human standing is modified by an unconscious integration of congruent sensory and motor signals. The Journal of Physiology. 2012;590(22):5783–5794. DOI: 10.1113/jphysiol.2012.230334.
22. Adkin AL, Campbell AD, Chua R, Carpenter MG. The influence of postural threat on the cortical response to unpredictable and predictable postural perturbations. Neuroscience Letters. 2008;435(2):120–125. DOI: 10.1016/j.neulet.2008.02.018.
23. Chang CJ, Yang TF, Yang SW, Chern JS. Cortical modulation of motor control biofeedback among the elderly with high fall risk during a posture perturbation task with augmented reality. Frontiers in Aging Neuroscience. 2016;8:80. DOI: 10.3389/fnagi.2016.00080.
24. Jacobs JV, Fujiwara K, Tomita H, Furune N, Kunita K, Horak FB. Changes in the activity of the cerebral cortex relate to postural response modification when warned of a perturbation. Clinical Neurophysiology. 2008;119(6):1431–1442. DOI: 10.1016/j.clinph.2008.02.015.
25. Mochizuki G, Sibley KM, Esposito JG, Camilleri JM, McIlroy WE. Cortical responses associated with the preparation and reaction to full-body perturbations to upright stability. Clinical Neurophysiology. 2008;119(7):1626–1637. DOI: 10.1016/j.clinph.2008.03.020.
26. Rodrick D, Jayaprakash V. Neural mechanisms of anticipatory balance control. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 2013;57(1):915–919. DOI: 10.1177/1541931213571203.
27. Tse YYF, Petrofsky J, Berk L, Daher N, Lohman E, Cavalcanti P, Laymon M, Rodrigues S, Lodha R, Potnis PA. Postural sway and EMG analysis of hip and ankle muscles during balance tasks. International Journal of Therapy and Rehabilitation. 2013;20(6):280–288. DOI: 10.12968/ijtr.2013.20.6.280.
28. Asai Y, Tateyama S, Nomura T. Learning an intermittent control strategy for postural balancing using an EMG-based human-computer interface. PLoS One. 2013;8(5):e62956. DOI: 10.1371/journal.pone.0062956.
29. Blaszczyszyn M, Konieczny M, Pakosz P. Analysis of ankle sEMG on both stable and unstable surfaces for elderly and young women-a pilot study. International Journal of Environmental Research and Public Health. 2019;16(9):1544. DOI: 10.3390/ijerph16091544.
30. Blenkinsop GM, Pain MTG, Hiley MJ. Balance control strategies during perturbed and unperturbed balance in standing and handstand. Royal Society Open Science. 2017;4(7):161018. DOI: 10.1098/rsos.161018.
31. Wang CC, Jiang BC, Huang PM. The relationship between postural stability and lower-limb muscle activity using an entropy-based similarity index. Entropy. 2018;20(5):320. DOI: 10.3390/e20050320.

32. Boonstra TW, Danna-Dos-Santos A, Xie HB, Roerdink M, Stins JF, Breakspear M. Muscle networks: Connectivity analysis of EMG activity during postural control. Scientific Reports. 2015;5(1):17830. DOI: 10.1038/srep17830.
33. Gebel A, Lüder B, Granacher U. Effects of increasing balance task difficulty on postural sway and muscle activity in healthy adolescents. Frontiers in Physiology. 2019;10:1135. DOI: 10.3389/fphys.2019.01135.
34. Noé F, García-Massó X, Paillard T. Inter-joint coordination of posture on a seesaw device. Journal of Electromyography and Kinesiology. 2017;34:72–79. DOI: 10.1016/j.jelekin.2017.04.003.
35. Rougier PR, Perennou D. Postural control in healthy young adults using a double seesaw device. Journal of Biomechanics. 2019;83:214–220. DOI: 10.1016/j.jbiomech.2018.11.048.
36. Lee D, Li Z, Sohail QZ, Jackson K, Fiume E, Agur A. A three-dimensional approach to pennation angle estimation for human skeletal muscle. Computer Methods in Biomechanics and Biomedical Engineering. 2015;18(13):1474–1484. DOI: 10.1080/10255842.2014.917294.
37. Moissenet F, Chéze L, Dumas R. A 3D lower limb musculoskeletal model for simultaneous estimation of musculo-tendon, joint contact, ligament and bone forces during gait. Journal of Biomechanics. 2014;47(1):50–58. DOI: 10.1016/j.jbiomech.2013.10.015.
38. Zhang J, Wu C, Wang Y. Human fall detection based on body posture spatio-temporal evolution. Sensors (Basel). 2020;20(3):946. DOI: 10.3390/s20030946.
39. Serra-Añó P, López-Bueno L, García-Massó X, Pellicer-Chenoll MT, González LM. Postural control mechanisms in healthy adults in sitting and standing positions. Perceptual and Motor Skills. 2015;121(1):119–134. DOI: 10.2466/26.25.PMS.121c10x4.
40. Polastri PF, Barela JA. Adaptive visual re-weighting in children's postural control. PLoS One. 2013;8(12):e82215. DOI: 10.1371/journal.pone.0082215.
41. Funato T, Aoi S, Tomita N, Tsuchiya K. Smooth enlargement of human standing sway by instability due to weak reaction floor and noise. Royal Society Open Science. 2016;3(1):150570. DOI: 10.1098/rsos.150570.
42. Hill AV. The heat of shortening and the dynamic constants of muscles. Proceedings of the Royal Society B: Biological Sciences. 1938;126(843):136–195. DOI: 10.1098/rspb.1938.0050.
43. Sanger TD. Bayesian filtering of myoelectric signals. Journal of Neurophysiology. 2007;97(2): 1839–1845. DOI: 10.1152/jn.00936.2006.
44. van Beers RJ, Haggard P, Wolpert DM. The role of execution noise in movement variability. Journal of Neurophysiology. 2004;91(2):1050–1063. DOI: 10.1152/jn.00652.2003.
45. Macefield G, Gandevia SC. Peripheral and central delays in the cortical projections from human truncal muscles. Rapid central transmission of proprioceptive input from the hand but not the trunk. Brain. 1992;115(1):123–135. DOI: 10.1093/brain/115.1.123.
46. Jeka J, Kiemel T. Modeling of Human Postural Control. In: Encyclopedia of Neuroscience. Springer, Berlin, Heidelberg; 2009. P. 2381–2384. DOI: 10.1007/978-3-540-29678-2.
47. Tresch M, Jindrich DL. Spinal and Neuromechanical Integration: Overview. In: Encyclopedia of Computational Neuroscience. Springer, New York; 2014. 3243 p. DOI: 10.1007/978-1-4614-7320-6.
48. Perry SD, Santos LC, Patla AE. Contribution of vision and cutaneous sensation to the control of centre of mass (COM) during gait termination. Brain Research. 2001;913(1):27–34. DOI: 10.1016/s0006-8993(01)02748-2.
49. Bottaro A, Yasutake Y, Nomura T, Casadio M, Morasso P. Bounded stability of the quiet standing posture: An intermittent control model. Human Movement Science. 2008;27(3):473–495. DOI: 10.1016/j.humov.2007.11.005.
50. Rahnami K, Arabshahi P, Gray A. Neural network based model reference controller for active queue management of TCP flows. IEEE Aerospace Conference. 5–12 March 2005, Big Sky, MT, USA. IEEE; 2005. P. 1696–1704. DOI: 10.1109/AERO.2005.1559464.

51. Swain PS, Longtin A. Noise in genetic and neural networks. Chaos. 2006;16(2):026101. DOI: 10.1063/1.2213613.
52. Ascher UM, Petzold LR. Computer Methods for Ordinary Differential Equations and Differential-Algebraic Equations. 1st edition. Society for Industrial and Applied Mathematics, USA; 1998. 332 p.
53. Berger DJ, d'Avella A. Effective force control by muscle synergies. Frontiers in Computational Neuroscience. 2014;8:46. DOI: 10.3389/fncom.2014.00046.
54. Pearson K. Notes on regression and inheritance in the case of two parents. Proceedings of the Royal Society of London. 1895;58(347–352):240–242. DOI: 10.1098/rspl.1895.0041.
55. Wilcoxon F. Individual comparisons by ranking methods. Biometrics Bulletin. 1945;1(6):80–83. DOI: 10.2307/3001968.



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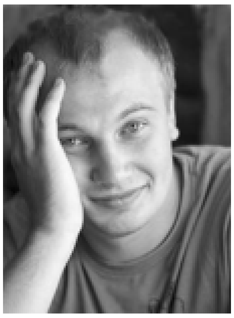

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