The difference of physiological signals between regular and occasional exercisers during cycling exercise

Ching-Ting Tseng [1], Chii-Wen Jao [1], Yen-Ling Chen [1], Chao-Wen Huang [1], Po-Shan Wang [1,2], Yu-Te Wu[1]
[1]Institution of Biophotonics, National Yang-Ming University, Taipei, Taiwan
[2]Department of Neurology, Municipal Gandau Hospital, Taipei, Taiwan

Abstract - *In this study, we investigated the difference of EEG, ECG and EMG signals collected during cycling exercise between regular exercisers and occasional exercisers. After five minutes resting, participants were asked to take cycling exercise at three stages in different loading. The EEG signal was analyzed by wavelet transform for nine frequency bands, delta, theta, low alpha, high alpha, low beta and high beta, low gamma, high gamma and whole frequency band form 0.5 Hz to 50 Hz. The ECG signal was used to calculate the average maximum heart rate ratio (AMHRR), DFA-α and Cardiac stress index (CSI) for evaluating the cardiac status during cycling exercising. The Wilcoxon Rank Sum Test was used to compare the differences between regular exercise and occasional exercise groups, and the multiple regression analysis was adopted to estimate the association between EEG power and AMHRR or RMS of EMG. The results of DFA-α, CSI, and heart rate presented the regular exercisers suffered less cardiac stress than the occasional exercisers during cycling exercise. On the other hands, there was no significant difference in EEG signal between the two groups. In addition, the results of the multiple regression analysis revealed the AMHRR was slightly associated with EEG signals.*

Keywords: EEG, ECG, EMG and exercise

1 Introduction

Regular physical exercise is associated with clear health benefits, and it is an important part of preventive strategies for health promotion [1]. In order to examine the neurobiological and physiological effects induced by exercise, a wide range of techniques has been used, ranging from electroencephalography (EEG), electromyography (EMG), electrocardiography (ECG), magnetoencephalography (MEG), to magnetic resonance imaging (MRI). For high temporal resolution and convenience to the clinicians, ECG, EMG and EEG are used to observe heartbeat, muscle status and brain activity respectively; in addition, the heart rate variability (HRV) analysis can precisely predict the status of heart at rest or during exercise [2, 3]. On the other hand, previous studies also showed that the power spectrum of EEG changed during prolonged exercise [5,6] and after long-term exercise [7], which may reflect the alteration in physical and mental status of subjects. Bailey et al. indicated that the relaxed condition of subject during exercise can be evaluated by the ratio of alpha and beta waves in EEG [4]. Furthermore, Cirillo et al. [8] also showed that less active adults had longer movement preparation in terms of reduced amplitude of the negative slow wave cortical potential in EEG and more delayed processing in EMG.

However, there are few studies investigating the physiological and neurobiological differences between regular and occasional exercisers during physical exercise. In this study, we aim to indicate the brain activity and the response of muscle and heart during cycling exercise, which is a safer exercise for patients with sports injuries [15-17], and an effective way for stroke and brain palsy patients to improve their motor functions and balance [18,19]. In the present study, the EEG was adopted to examine the neural oscillations in the alpha, beta, theta, and gamma frequency domains [20]. The ECG, used to detect the multistage exercise (Simoons and Hugenholtz), was applied by the detrend fluctuation analysis and cardiac stress evaluation. The ECG signal was used to establish the average maximum heart rate ratio (AMHRR), which is inversely proportional to target heart rate and used to represent the cardiac strength grade. The EMG, as a tool for monitoring the skeletal muscle force, was used to quantify proper loading. Hence, we hypothesized that the different patterns of regular and occasional exercisers during cycling exercise could be indicated by these modalities.

2 Material and methods

2.1 Subjects and experimental protocol

Thirty-three healthy subjects (male: 15, female: 18, age: 22.15±3.6 years) participated in this study. All participants were verified they had no cardiovascular or chronic diseases. Before the experiment, each participant had signed an informed-consent approved by the Institutional Review Board (IRB). The participants were separated into two groups based on the time they spent in exercise every week, the ones who spent more than 3 hours every week are considered as the regular exerciser group (10 male and 10female), and the ones who spent less than 3 hours every week are regarded as occasional exerciser group (5 male and 8 female). Each subject was asked to sit on a bicycle and there were two sessions in the cycling experiment: the pretest session and experiment session. In the pretest session, each subject was asked to pedal 40 seconds at the speed of 75 rpm and rest 20 seconds in each section. The cycling load was remained constant at each section and increased in the next section. The participant had to finish 10 sections in the pretest session, in which the load was increased from the lightest to the heaviest from the first to the tenth sections. After the pretest session, the participants took 5 minutes rest. The EMG power of each section was calculated immediately and the load that corresponded to the maximum EMG power was considered as the subject-specific maximum load. The load that corresponded to 40% of maximum EMG power was defined as the subject suitable load.

In the experiment session, EEG and ECG were first recorded for 5-minutes resting with eye opening (Rest 1). In the subsequent three 5-minute cycling exercise sections, there were two 30-seconds rest sections in between. Each participant was asked to pedal at 75 rpm with the load lighter than his/her personal suitable load (stage 1), the subject suitable load (stage 2), and the load heavier than the personal suitable load (stage 3). After the stage 3, each subject took the final rest for 5 minutes (Rest 2). Accordingly, the experiment was proceeded in the following order: Rest 1, stage 1, 30-seconds rest, stage 2, 30-seconds rest, stage 3, and Rest 2. The EEG, ECG and EMG signals were collected at Rest 1-2 and stage 1-3 (Fig. 1).

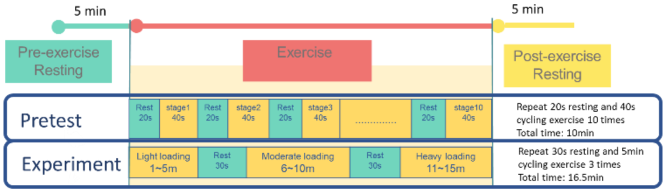

Figure 1. Pretest and experiment sessions.

2.2 EMG, ECG and EEG data acquisition

The EEG was recorded using VAmp amplifier (Brain Products GmbH, Munich, Germany) with 1KHz sampling rate in which only 9 electrodes, namely, F3, F4, Fz, C3, C4, Cz, P3, P4, Pz, and A1 were used according to the international 10/20 system (Fig. 2). The left mastoid was used as reference for all electrodes and the ground electrode was placed on FPz. Impedances of the EEG was kept below 20 kΩ during the recording. The ECG and EMG are also collected by Vamp amplifier with bipolar electrodes.

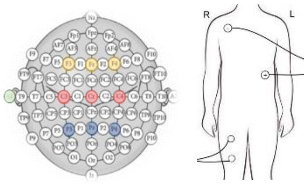

Figure 2. The experimental setup. Participants were equipped with 9 EEG channels, 2 EMG channels for rectus femoris muscle and 2 ECG channels.

2.3 EEG processing

The EEG signals were bandpass-filtered between 0.5 and 50 Hz for each subject and detrended by the median filter. The data were segmented into one-minute segments which were proceeded by the Morlet wavelet transform for nine frequency bands, namely, delta (1-4 hz), theta (4-8 Hz), low alpha (10-12 Hz), high alpha (21-30 Hz), low beta (13-21 Hz), high beta (21-30 Hz) low gamma (30-45 Hz), high gamma (45-60 Hz) and the frequency from 0.5 Hz to 50 Hz. The power in each of the nine frequency bands was summed and divided by the power of corresponding frequency band of the resting section before cycling exercise. The Morlet wavelet was proposed by Morlet and Grossmann in the 1980s [14]. The definition of Morlet wavelet is as follows:

$$WT(a,b) = \int_{-\infty}^{\infty} x(t)\varphi_{(a,b)}(t)dt \quad (1)$$

where

$$\mathrm{w(s,r)} = \frac{1}{\sqrt{|s|}}\int x(t)\,\varphi^{*}(\frac{t-\tau}{s}) \quad (2)$$

is the mother wavelet, x(t) is a continuous time signal, a is a dimensionless frequency scale variable, and b is a time-like translation variable.

2.4 ECG processing

The ECG signals of each subject were band-stop filtered between 55 and 65 Hz. Every R-R interval was used to calculate the heart rate. We further used the average maximum heart rate ratio (AMHRR) to monitor the status of each subject during the experiment. The AMHRR was defined as follows:

$$\mathrm{AMHRR} = \frac{\text{averaged heart rate in each stage}-RHR}{\text{predicted maximal heart rate (220}-\text{age}-\text{RHR)}} * 100\% \quad (3)$$

where RHR is the averaged heart rate during resting.

The Detrend Fluctuation Analysis (DFA) and Cardiac Stress Index (CSI) [21] are commonly used methods to evaluate the cardiac stress. DFA can quantitatively characterize the complexity of time series using the fractal theory. The steps of DFA computation is summarized as follows. Let x represent a time series of R-R intervals and $\bar{x}$ the average of x, we calculate an integrated time series y which is given by

$$\mathrm{y(k)} = \sum_{i=1}^{k}[x(i) - \bar{x}] \quad (4)$$

The time series y is further divided into segments with the length of each segment being n. Each segment is fitted by a least squared line, denoted by y_n. The time series y can be detrended locally by each y_n and we can calculate the root mean square of the resulting fluctuation, y - y_n. The root-mean-square based fluctuation is denoted as F(n) and given by

$$\mathrm{F(n)} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_n(k)]^2} \quad (5)$$

The calculation in (5) is repeated for all possible values of n so that a linear relationship between log F(n) and the time scale log n can be established to compute the slope α as follows

$$\alpha = \frac{log_{10}\mathrm{F(n)}}{log_{10}\mathrm{(n)}} \quad (6)$$

where n is ranged from 4 to 64 in this study

The CSI can be calculated based on α and given by

$$\mathrm{CSI} = \frac{Number\ of\ events\ with\ \alpha\ \text{lower than 1}}{Total\ number\ of\ events} \quad (7)$$

2.5 EMG processing

The root mean square (RMS) of EMG signal is often used as a concise quantitative index of muscle activity. It can be expressed as

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{8}$$

where x_n represents the EMG signal.

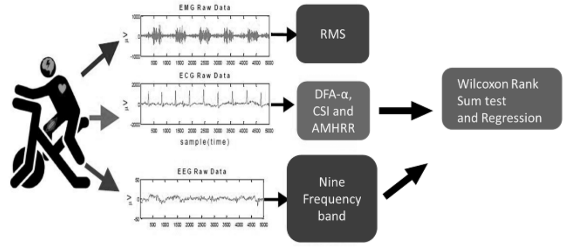

Figure 3. The processing of EEG, ECG and EMG in this study

2.6 Statistical analysis

The Wilcoxon Rank Sum Test was used to evaluate the differences between regular exercise and occasional exercise groups. In addition, the multiple regression analysis was adopted to estimate the association between EEG power and AMHRR or RMS of EMG.

3 Results

The heart rates and the AMHRR of both groups are presented on Table 1. The heart rates and the AMHRR increased as the exercise intensity increased in both groups. In addition, the occasional exercisers exhibited faster heart rate but smaller AMHRR than the regular exercisers. The inconsistence between heart rate and AMHRR between two group may result from that the occasional exerciser group (22.42 ± 3.9years) is elder than the regular exerciser group (21.72 ± 2.4years). The result suggested that the occasional exerciser group suffered from more cardiac stress while taking cycling exercise.

Table1. The heart rate and AMHRR

Heart rate	Rest1	Stage1	Stage2	Stage3
Frequency Exercise	88.5±12.7	124.6±16.7	138.2±16.7	148.1±18.0
Less Frequency Exercise	88.5±10.9	132.3±19.5	144.0±20.9	156.9±22.8
AMHRR	**Rest1**	**Stage1**	**Stage2**	**Stage3**
Frequency Exercise		39.7±16.1	50.6±16.7	62.4±18.4
Less Frequency Exercise		32.7±13.7	45.3±14.3	54.7±15.2

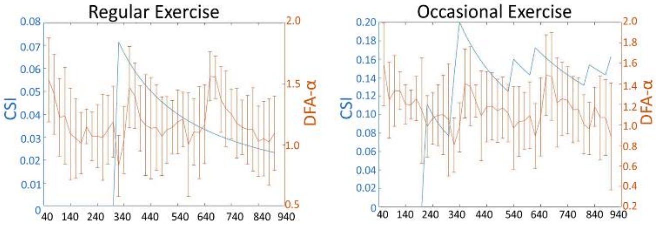

Figure 4. The results of DFA-α and CSI in regular exercise group and occasional exercise group. (Left: Figure 4A illustrates the pattern of the regular exerciser group. Right: Figure 4B illustrates the pattern of the occasional exerciser group.)

Figure 4A and 4B demonstrate the results of DFA-α (red curves with standard deviations) and CSI (blue curve) analysis for regular and occasional exercisers. In general, the regular exercisers exhibited higher DFA-α and lower CSI than the occasional exercisers. Moreover, the CSI curve of the regular exercisers increased late at 300 seconds and diminished gradually after it reached the peak. However, the CSI curve of the occasional exercisers raised early at 200 seconds and not reached the peak directly. Then, during the declination period, the CSI curve decreased slightly with sporadic raise.

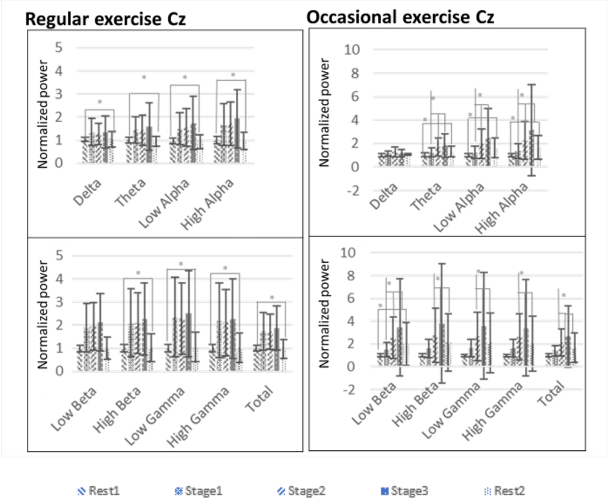

Figure 5. The results of the normalized power of EEG. (Left: Figure 5A illustrates for the regular exerciser group. Right: Figure 5B illustrates for the occasional exerciser group.)

Figure 5A and 5B demonstrates the results of the normalized power of different spectrum in EEG for regular exercisers and occasional exercisers. Generally, almost all of the frequency bands in Cz showed significantly different ($p<0.05$) only between the two resting stages before and after exercise in the regular exercise group. Apart from the normalized power of delta band, the occasional exercise had significantly different ($p<0.05$) power in Cz between every nearby stage (i.e. Rest1-Stage1, Stage1-Stage2, and so on). However, the normalized power in other channels of the regular exercisers were higher but not significantly than the occasional exercisers. There was also no difference between groups in every stage and every frequency band. Furthermore, the results of the multiple regression analysis, the changes of normalized EEG power were slightly correlated with AMHRR.

4 Conclusions

In the present study, both the results in the EEG and ECG demonstrated that the occasional exercisers required longer adaptation time on the cardiac and neurobiological responses to physical exercise. The occasional exercisers had greater cardiac stress than the regular exercisers because of higher heart rate and higher DFA- α. The changes of CSI through cycling reflected the difference in adaption to exercise between groups of regular exercise and occasional exercise. The occasional exercisers, who may have less motor memory in the coordination of different muscles and respiratory rhythm, took early and more efforts to accomplish the physical task with the same loading to individual subject, as the CSI curve raised early and decreased slightly with sporadic raise as shown in Figure 4B.

On the other hand, although the group with or without habit of exercise had no different normalized EEG power in every stage and every frequency band, the within-group changing patterns in almost all the frequency bands were different between groups. That is, different normalized EEG power only occurred in the comparison of two resting stages before and after exercise in the regular exerciser, who had only slight alteration of the nearby stages. The results represented that the regular exerciser called up appropriate strength in the very begin of exercise. Nevertheless, as the occasional exercisers showing different EEG power between every nearby stage, the results could imply that the occasional exercisers accommodate the multifold capabilities that were needed for exercise while they do this physical performance.

In the future, mood status and cognitive function may be needed to examine the relationship between the findings in the present study and different performance, and to provide stronger evidence for the neurobiological effects of exercise.

5 Acknowledgments

This study was supported by the grant from the Ministry of Science and Technology, Taiwan (MOST 106-2221-E-010 -016 -MY3).

6 References

[1] H. Boecker, A. Drzezga. “A perspective on the future role of brain pet imaging in exercise science,” NeuroImage, vol. 131, pp. 73–80, May 2016.

[2] Y. Yamamoto, R. L. Hughson, and J. C. Peterson, “Autonomic control of heart rate during exercise studied by heart rate variability spectral analysis,” J. Appl. Physiol. Bethesda Md 1985, vol. 71, no. 3, pp. 1136–1142, Sep. 1991.

[3] R. Perini and A. Veicsteinas, “Heart rate variability and autonomic activity at rest and during exercise in various physiological conditions,” Eur. J. Appl. Physiol., vol. 90, no. 3–4, pp. 317–325, Oct. 2003.

[4] S. P. Bailey, E. E. Hall, S. E. Folger, and P. C. Miller, “Changes in EEG During Graded Exercise on a Recumbent Cycle Ergometer,” J. Sports Sci. Med., vol. 7, no. 4, pp. 505–511, Dec. 2008.

[5] F. Gomez-Pinilla and C. Hillman, “The influence of exercise on cognitive abilities,” Compr. Physiol., vol. 3, no. 1, pp. 403–428, Jan. 2013.

[6] R. Meeusen, “Exercise, Nutrition and the Brain,” Sports Med. Auckl. Nz, vol. 44, no. Suppl 1, pp. 47–56, 2014.

[7] M. T. Lardon and J. Polich, “EEG changes from long-term physical exercise,” Biol. Psychol., vol. 44, no. 1, pp. 19–30, Sep. 1996.

[8] J. Cirillo, B. Finch, G. Ansonab. “The impact of physical activity on motor preparation in young adults,” Neuroscience Letters, vol. 638, pp. 196-203, Jan. 2017.

[9] X. Yu, C. Zhang, and J. Zhang, “Causal interactions between the cerebral cortex and the autonomic nervous system,” Sci. China Life Sci., vol. 57, no. 5, pp. 532–538, May 2014.

[10] J. A. Faulkner, S. V. Brooks, and E. Zerba, “Skeletal muscle weakness and fatigue in old age: underlying mechanisms,” Annu. Rev. Gerontol. Geriatr., vol. 10, pp. 147–166, 1990.

[11] M. P. Amato, G. Ponziani, F. Rossi, C. L. Liedl, C. Stefanile, and L. Rossi, “Quality of life in multiple sclerosis: the impact of depression, fatigue and disability,” Mult. Scler. J., vol. 7, no. 5, pp. 340–344, Oct. 2001.

[12] M. H. De Groot, S. J. Phillips, and G. A. Eskes, “Fatigue associated with stroke and other neurologic conditions: Implications for stroke rehabilitation,” Arch. Phys. Med. Rehabil., vol. 84, no. 11, pp. 1714–1720, Nov. 2003.

[13] S. Merkelbach, H. Sittinger, and J. Koenig, “Is there a differential impact of fatigue and physical disability on quality of life in multiple sclerosis?,” J. Nerv. Ment. Dis., vol. 190, no. 6, pp. 388–393, Jun. 2002.

[14] W. Morley, K. Jackson, and G. E. Mead, “Post-stroke fatigue: an important yet neglected symptom,” Age Ageing, vol. 34, no. 3, pp. 313–313, May 2005.

[15] H.-Y. Chen, S.-C. Chen, J.-J. J. Chen, L.-L. Fu, and Y. L. Wang, “Kinesiological and kinematical analysis for stroke subjects with asymmetrical cycling movement patterns,” J. Electromyogr. Kinesiol. Off. J. Int. Soc. Electrophysiol. Kinesiol., vol. 15, no. 6, pp. 587–595, Dec. 2005.

[16] D. A. Brown, S. A. Kautz, and C. A. Dairaghi, “Muscle activity adapts to anti-gravity posture during pedalling in persons with post-stroke hemiplegia,” Brain J. Neurol., vol. 120 (Pt 5), pp. 825–837, May 1997.

[17] J. C. Rosecrance and C. A. Giuliani, “Kinematic analysis of lower-limb movement during ergometer pedaling in hemiplegic and nonhemiplegic subjects,” Phys. Ther., vol. 71, no. 4, pp. 334–343, Apr. 1991.

[18] M. Katz-Leurer, I. Sender, O. Keren, and Z. Dvir, “The influence of early cycling training on balance in stroke patients at the subacute stage. Results of a preliminary trial,” Clin. Rehabil., vol. 20, no. 5, pp. 398–405, May 2006.

[19] H. Williams and T. Pountney, “Effects of a static bicycling programme on the functional ability of young people with cerebral palsy who are non-ambulant,” Dev. Med. Child Neurol., vol. 49, no. 7, pp. 522–527, Jul. 2007.

[20] E. Başar, B. T. Gölbaşı, E. Tülay, S. Aydın, C. Başar-Eroğlu. “Best method for analysis of brain oscillations in healthy subjects and neuropsychiatric diseases,” Int. J. Psychophysio., vol. 103, pp. 22-42, May 2016.

[21] B. Makivic and P.Bauer, “Variability analysis in sport,” sport medicine journal vol4 326-331, 2015

[22] C. H. Hsu et al., “Poincaré plot indexes of heart rate variability detect dynamic autonomic modulation during general anesthesia induction,” Acta Anaesthesiol. Taiwan., vol. 50, no. 1, pp. 12–18, Mar. 2012.