ISSN: 2586-6036 © 2022 KODISA & JWMAP.
http://www. welfareconvergence.or.kr
doi: http://dx.doi.org/10.13106/jwmap.2022.Vol5.no2.15

Extraction of Motor Modules by Autoencoder to Identify Trained Motor Control Ability

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Received: April 22, 2022. Revised: June 3, 2022. Accepted: June 10, 2022.

Abstract

Purpose: This pilot study aimed to clarify features of motor module during walking in exercise experts who experienced lately repeated training for sports skill. To identify motor modules, autoencoder machine learning algorithm was used, and modules were extracted from muscle activities of lower extremities. **Research design, data and methodology:** A total of 10 university students were participated. 5 students did not experience any sports training before, and 5 students did experience sports training more than 5 years. Eight muscle activities of dominant lower extremity were measured. After modules were extracted by autoencoder, the numbers of modules and spatial muscle weight values were compared between two groups. **Results:** There was no significant difference in the minimal number of motor modules that explain more than 90% of original data between groups. However, in similarity analysis, three motor modules were shown high similarity (r>0.8) while one module was shown low similarity (r<0.5). **Conclusions:** This study found not only common motor modules between exercise novice and expert during walking, but also found that a specific motor module, which would be associated with high motor control ability to distinguish the level of motor performance in the field of sports.

Keywords : Autoencoder, Exercise experts, Machine learning, Motor module, Walking, Sports

JEL Classification Codes : I10, I30, I31

1. Introduction

Human body produces various movements with coordination and simultaneous activation of several muscles (Diedrichsen, Shadmehr, & Ivry, 2010). All movements have numerous degrees of freedom depending on the joint plane that implied a complexity of motor control, which called the degrees of Freedom problem (Berstein, 1967). Therefore, it has been difficult to explain the mechanisms of the central nervous system (CNS) that control sophisticated movements.

* Acknowledgements: This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No.2020R1I1A1A0107544511)
* Conflict of interest statement: We hereby confirm that the manuscript has no actual or potential conflict of interest with any parties, including any financial, personal or other relationships with other people or organizations within three years of beginning the submitted work that could inappropriately influence or be perceived to influence. We confirm that the paper has not been published previously, it is not under consideration for publication elsewhere, and the manuscript is not being simultaneously submitted elsewhere.

Many recent studies have been supported a theory that CNS would control the movements through a flexible combination of individual muscles, which called motor module (d'Avella, 2016; Israely, Leisman, & Carmeli 2018). According to previous findings, in motor module, individual muscles are activated simultaneously like a team (Bizzi & Cheung, 2013) that simplify diverse and complex high-dimensional movements (Berniker, Jarc, Bizzi, & Tresch, 2009).

In particular, walking is a representative function that requires high-degree coordination of upper and lower extremities, and has been studied in many studies to understand motor control mechanism (Esmaeili, Karami, Baniasad, Shojaeefard, & Farahmand, 2022). In a healthy population, more than 90% of muscle activities of the lower limb during walking was explained by 4 to 5 motor modules (Barroso et al., 2014; Ivanenko, Poppele, & Lacquaniti, 2004) and the number of these motor modules were consistent regardless different walking conditions, such as in walking backwards (Ivanenko, Cappellini, Poppele, & Lacquaniti, 2008), in walking with different speed (Ivanenko et al., 2004), and even in running (Ivanenko et al., 2008). These findings indicated that human walking-related physical activities would share common mechanism of motor control.

Furthermore, motor module studies have been conducted for patients with the impaired nervous system (Clark, Ting, Zajac, Neptune & Kautz, 2010). According to the results of previous studies, patients with stroke showed pathological features in motor modules, unlike normal people (Routson, Kautz, & Neptune, 2014; Clark et al., 2010). In the case of patients with incomplete spinal cord injury, it was confirmed that the number of motor modules decreased (Hayes, Chvatal, French, Ting, & Trumbower, 2014). This pathological feature of motor module in patients indicated that motor modules would be merged by certain neurological damages.

Whereas, in case that CNS has higher motor control ability than normal people, features of the motor module have been rarely studied. For example, people who repeatedly train to acquire exercise skills would have outstanding motor control ability from vision to perception systems compared to the normal (Taborri, Agostini, Artemiadis, Ghislieri, Jacobs, Roh, & Rossi, 2018). Therefore, this study aimed to clarify features of motor module during walking in exercise experts who experienced lately repeated training for specific sports performance. To identify motor modules, autoencoder machine learning algorithm was used and modules were extracted from muscle activities of lower extremities.

2. Literature Review

2.1. Motor Module in Biomechanics

High dimension of data of muscle activities, which measured by electromyogram (EMG) is reduced to low dimension using autoencoder algorithms. The reduced data is interpreted as motor modules in biomechanics. Autoencoder extracts motor modules by reconstructing the original EMG data with the reduced data to be as similar as possible (Hug, 2011). The reconstruction quality was evaluated by variance of accounted for (VAF). From a mathematical point of view, one motor module is a matrix which could decomposed to two components, the first being called a “spatial muscle weights", which shows how much individual muscles contribute to a motor module. The second is called "temporal muscle activation", which shows the time-varying magnitude of motor modules.

3. Methodology

3.1. Participants

In this study, a total of 10 university students were participated. 5 students did not experience any sports training before and 5 students did experience sports training more than 5 years to being athletes. Demographics of participants are presented in Table 1. All participants were informed of the study and consented to participate before the experiment. The experimental procedure was approved from the Research Ethics Committee (KUIRB2018- 0127).

Table 1: Participant demographics

n=10	Novice (n=5)	Experts (n=5)
Sex (male/female)	2/3	1/4
Age (years)	21.32 ± 2.96	22.96 ± 1.47
Height (cm)	162.58 ± 1.05	164.92 ± 3.30
Weight (kg)	55.40 ± 2.18	56.28 ± 3.05
Skeletal muscle mass (kg)	25.25 ± 2.61	27.85 ± 1.80
Body fat mass (%)	28.65 ± 2.43	24.21 ± 1.97
BMI (kg/m^2)	25.36 ± 4.32	23.90 ± 3.10

3.2. Experimental Procedure

All participants performed 20-cycle walking tasks on the 8m long straight line with self-selected speed. During the walking task, eight muscle activities of dominant leg were collected at 1000Hz in real-time using a surface electromyogram (Noraxon Telemyo DTS, USA). The measured muscles were as follows: adductor longus (ADL), biceps femoris (BF), gastrocnemius (GC), gluteus maximus (GM), rectus femoris (RF), Semitendinosis (ST), tibialis anterior (TA), vastus medialis (VM). The detailed EMG attachment methodology was presented in the author's previous study (Lee, 2021).

3.3. Data Analysis

All data analysis was conducted using MATLAB (version R2017a, USA). All raw EMG data were filtered by a high-pass filter (35 Hz, fourth-order Butterworth filter), rectified and fileted again by a low-pass filter (5 Hz, fourth-order Butterworth filter). Then, the filtered data was segmented per walking cycle from heel contact to toe-off phase, and then each cycle interpolated to 200 time-points. Lastly, after the data of each cycle was normalized to the peak value of each muscle activity, all segmented data were again concatenated as the input data for autoencoder per muscle. Then, motor modules were finally extracted from the concatenated data for two groups.

3.4. Statistical Analysis

The difference in the average number of extracted motor modules between two groups was tested by Mann-whitney U test. The similarity of spatial muscle weights of motor module between two groups was tested by Pearson correlation coefficient. If correlation coefficient (r) is more than 0.7, it means that two motor modules between the group are similar (Chvatal and Ting, 2013). In addition to statistical test, major component muscles per each motor module were compared. The inclusion criteria for the major component muscles of each motor module was muscles with a weight value, corresponding to more than 80% of the maximum weight value in each motor module (Steele et al., 2013). All statistical P-value were set to 0.05, and analysis was conducted using SPSS (Version 19, USA).

4. Results

4.1. Number and VAF of Motor Modules between Groups

The minimum number of motor modules with more than 90% of VAF was extracted from exercise novice and expert group using autoencoder algorithm. As a result, averaged number of motor modules in the two groups was 4.40 ± 0.55 for novices and 4.60 ± 0.55 for experts, showing no statistically significant difference (Table 2).

Table 2: The number of motor modules between exercise novices and experts

	Novices	Experts	P-value
Number of modules	4.40 ± 0.55	4.60 ± 0.55	0.56
VAF	91.20 ± 1.30	92.40 ± 0.89	0.19

4.2. Spatial Muscle Weights of Motor Modules between Groups

For analyzing the similarity between motor modules, the extracting number of motor modules was set to 4 prior to operation of autoencoder algorithm. After extraction, four modules were defined according to methodology introduced by Lee (2022). Then, the similarity of averaged spatial muscle weights of four motor modules during walking in novice and expert group was analyzed using Pearson correlation coefficient. The results were shown in table 3.

Table 3: Similarity of spatial muscle weights between novice and expert during walking

Muscles	Module 1	Module 2	Module 3	Module 4
Coefficient	0.942*	0.832*	0.917*	0.414

Note: * Significant level, P<0.05

5. Discussion

Functional movements are produced through muscle coordination, and motor modules are used to control muscle coordination (Chavatal and Ting, 2013). This study aimed to observe features of motor modules of exercise experts during walking by comparing modules of exercise novices.

First, in terms of the number of motor modules, there was no significant difference between two groups. Both groups showed the number of extracted motor modules in range of four to five that was consistent with the results of previous studies (Barroso et al., 2014; Clark et al., 2010; Ivanenko et al., 2004).

In analyzing the similarity of spatial weight values of each motor module between the groups, three motor modules of four modules were significantly similar between the groups and the following clinical interpretation would be possible based on a previous study (Lee, 2022). In motor module 1, which was activated during the early stance phase with the prominent spatial weight values of hip and knee extensor (GM and VM), and ankle dorsiflexor (TIB) were prominent and both groups showed similar feature of motor module. It meant that exercise training would not specially influence initial foot contact during early phase for walking. Therefore, this interpretation would apply to the rest motor modules like module 2, which activated during the mid to late stance phase with the prominent spatial weight values of TA, and module 3, which activated during the early swing phase with the prominent spatial weight values of RF and ADL.

Unlike motor modules 1, 2 and 3, motor module 4 was shown the lowest similarity. According to a previous study by the author, motor module 4 was activated during late swing phase with the prominent spatial weight values of SEM, BFM. That is, it means that exercise experts with high motor control ability by training would have the outstanding control ability to decelerate functional movements and convert the next motion quickly. Furthermore, the control ability to decelerate the movement would be deeply associated with an ability to prevent the injury during physical activity (Fort- Vanmeerhaeghe, Romero-Rodriguez, Lloyd, Kushner, & Myer, 2016; Kovacs, Roetert, & Ellenbecker, 2008). Therefore, it could be seen that the results of this study provide a clue that the outstanding motor control ability of exercise experts is resulted from motor module 4.

However, since there is a potential limitation to interpret the results of this study because of small sample size, future studies with large sample size are necessary for strong evidence. Furthermore, if motor module 4 was a key factor to distinguish the level of motor control ability, reinforcement strategy of motor module 4 will be also studied in the future.

6. Conclusions

In this study, it was confirmed that there is three common motor modules and one specific motor module between exercise novice and expert groups. Further studies will be necessary to confirm the characteristic motor module to distinguish the outstanding motor control ability and provide a basis for reinforcement and rehabilitation of motor modules especially for patients with CNS damages.

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