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보행 과정에서 발생하는 복합 근육 활성의 양성 및 음성 공변 메커니즘

Positive and Negative Covariation Mechanism of Multiple Muscle Activities During Human Walking

김유신*, 홍영기**
한국과학기술원 신경재활공학연구실*, 청주대학교 스포츠의학과**

Yushin Kim(yushinkim@kaist.ac.kr)*, Youngki Hong(spinehong@gmail.com)**

요약

보행 과정에서 여러 근육이 동시에 수축하는 운동 모듈 또는 근육 시너지는 매우 중요한 중추신경계 운동 조절 메커니즘이다. 본 연구는 걷는 동안 근육 간 양성 및 음성 공변 패턴을 이해하는 것을 목표로 한다. 본 연구에서는 트레드밀 보행 시 발생하는 다리 근육 활성을 근전도 검사를 통해 측정하였다. 동시 수축 근육 그룹, 즉 운동 모듈을 확인하기 위해 우리는 양쪽 4 개의 다리 근육(전경골근, 내측 비복근, 대퇴직근, 내측 슬괵근)에서 근전도 데이터를 수집하였고, 이를 바탕으로 비음수행렬분해 및 주성분 분석을 수행하였다. 이후 근육 또는 운동 모듈 간의 다양한 조합으로부터 공변이 값을 계산하였고, 이원배치분산분석을 이용하여 각 조합들에서 발생하는 공변이 패턴을 비교하였다. 그 결과, 다양한 조합 사이에 유의미한 공변이 값의 차이가 발견되었다($p < 0.05$). 같은 운동 모듈로 정의된 특정 근육 사이에서 발생하는 근 활성은 양성 공변이를 보여주었으나 운동 모듈 사이에서는 음성 공변이를 보여주었다. 모든 근육 조합들 사이에서는 음성 공변이가 발생하였다. 운동 모듈 사이에서 안정적으로 발생하는 음성 공변이는 운동 모듈이 복잡한 운동 조정의 제어 단위(control unit) 일 수 있음을 암시하고 있다.

■ 중심어 : | 근육 동시 수축 | 보행 | 공변이 | 비음수행렬분해 | 주성분 분석 |

Abstract

In human walking, muscle co-contraction which produces simultaneous activities of multiple muscles is important in motor control mechanism of the central nervous system. This study aims to understand positive and negative covariation mechanism of inter-muscle activities during walking. In this study, we measured electromyography (EMG) in leg muscles. To identify motor modules, we recored EMG from 4 leg muscles bilaterally (the tibialis anterior, medial gastrocnemius, rectus femoris and medial hamstring muscles) and performed non-negative matrix factorization (NMF) and principa component analysis (PCA). Then, we computed covariation values from various combinations between muscles or motor modules and used two-way repeated measures analysis of variance to identify significantly different covariation patterns between muscle combinations. As the results, we found significant differences between covariation values of muscle combinations ($p < 0.05$). muscle groups within the same motor modules produced the positive covariations. However, there were strong negative covariation between motor modules. There was negative covariation in all muscle combination. Stable inter-module negative covariation suggests that motor modules may be the control unit in the complex motor coordination.

■ keyword : | Muscle Co-contraction | Walking | Covariation | Non-negative Matrix Factorization | Principle Component Analysis |

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I. INTRODUCTION

Similar structural constraint of neuro-musculo-skeletal system among human beings allows an existence of specifically patterned walking strategies [1][2]. Meanwhile, because of a number of spatiotemporal degree of freedom in the neuro-musculo-skeletal system, the synergy between individual joints would vary in the process of whole body movement by motor abundance[3][4]. That is, although the way to move forward in normal gait cycle is similar between gait cycles and human beings, various motor control strategies might be required to maintain balance and upright posture in walking[1][2].

To stabilize the whole body kinematics, human beings should control a number of each joint movement concurrently during walking. In whole body coordination, the movements of individual joints are variable, but the sum of each joint movement is much more stabilized by compensatory synergies[5]. Even if one local joint movement is reduced after musculoskeletal injury, total joint movement is preserved by increased movement of the other joints during locomotion[6]. These facts indicate a reverse relationship of inter-joint kinematics, namely negative compensatory synergy, as one joint movement increases by decrease of other joint[6].

In the process of inter-joints coordination, corresponding muscle activities are positively necessary. However, it has been widely accepted that muscle co-contraction which produces simultaneous activities of both agonist and antagonist muscles around same joint is important to increase joint stability[7-10]. That is, the synergy in muscular level may have positive compensatory synergy pattern as one muscle activity increases by increase of other muscles[10]. Yet, it is necessary to deliberate identifying the positive compensatory synergy especially in case of walking because the reciprocal inhibition mechanism between the agonist and antagonist is surrounded in the same joint[11].

By a linear decomposition technique, the positive compensatory synergy of muscle activities, motor module, have been shown in human walking[2][12]. Because the motor module is composed across multi-segmental muscles[1][2][12], the mechanism would be different with the agonist and antagonist co-contraction[10]. It has been assumed that the motor module in body segments may result from common neural pathways[13][14]. If the motor module reflects constraint source of human motor redundancy by neural mechanism[15], the muscle activities within each module would produce the positive compensatory synergy across multi-segments to simplify movement production. Moreover, because muscle compositions within the motor module are fixed[16], the muscular covariation patterns would be stable during a number of gait cycles. As some investigators have asserted that the muscle groups are flexibly consisted in various muscle combinations during functional postures or movements and not to work together[17][18]. Thus, it also should be identified whether the positive compensatory synergy is produced between fixed muscles comprising the motor module.

The purpose of the study was to understand covariation mechanism of inter-muscle activities during walking. To identify the mechanism, first, the positive or negative covariation values were demonstrated from inter-muscle activities using electromyography (EMG) during consecutive walking. According to the motor module concept, we hypothesized that the muscle activities would show the positive covariation within each module, but not in between-module combinations. In case of agonist-

antagonist pairs, we expected that the positive covariation would be blocked by reciprocal inhibition. If no significant positive covariation would be identified in the study, it means that the combination of the muscle groups within the module is not clear. More specifically, we also considered the possibility of positive covariation with reverse relationship between elements[Fig. 1]. In this case, the elements are worked simultaneously with the same shape in the work space, but the signals were formed with reverse shape from its mean value. Hence, we identified existence of this pattern in process of forming the reverse synergy in mean-corrected space.

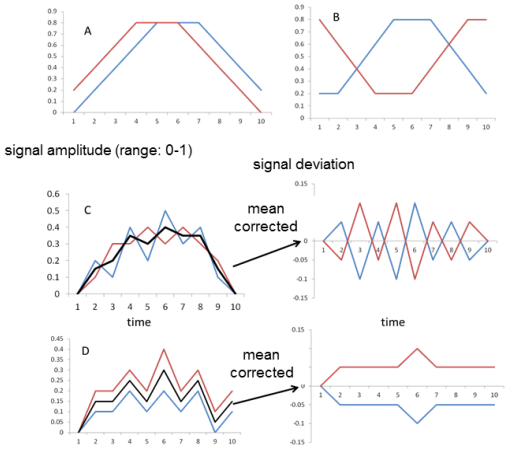

Fig. 1. Examples of covariation patterns

Black line indicates mean value between the elements. A) positive covariation, B) negative covariation, C) positive covariation in work space & high variance in mean-corrected space, D) positive covariation in work space & low variance in mean-corrected space.

II. METHODS

2.1 Participants

Participants in this study included sixteen healthy adults (8 females and 8 males; age, 25.3 ± 5.4 yr; body mass, 76.1 ± 14.1 kg; height, 170.2 ± 11.5 cm; dominant side, right). Participants were included if they had no medical history regarding musculoskeletal or neurological disease. Exclusion criteria were : (1) acute musculoskeletal injury, (2) neurological history, (3) problems in ambulation, (4) pregnancy, and (5) amputation. All participants had the experience to walk without any supports in a treadmill. Study procedures were approved by the institutional review board of Cheongju University (HR-013-01).

2.2 Procedures

Surface EMG (BTS FREEEMG, Milan, Italy) was measured during walking. Electrodes were placed on the tibialis anterior, medial gastrocnemius, rectus femoris and medial hamstring (semitendinosus) muscles bilaterally. These muscles were selected due to their apparent and robust activities during walking in a previous study[12].

Inter-electrode distance was 20 mm. Before attaching the electrode, the skin areas were cleaned with alcohol. Sampling rate of EMG was 1000 Hz. To confirm EMG activities, visual inspection was conducted during voluntary submaximal movements for each muscle in standing position. To avoid EMG noise generated by motion artifacts, all EMG signals were pre-amplified and the hardware low pass filter was fixed at 450 Hz. EMG data were processed using a third-order high-pass Butterworth filter at 30 Hz, full-wave rectification, a third-order low-pass Butterworth filter at 5 Hz. A synchronized triaxial accelerometer was used to decide individual gait cycles and placed over the shank to identify heel strike event of right leg side. Participants walked on a treadmill (STEX8100T, TaeHa, Korea). They were

given 1 - 2 min to familiarize themselves. After the familiarization with the device and pace, participants walked at 3 km/h with no inclination for 3 min while data were recorded[1].

2.3 Motor module extraction

EMG data were extracted for consecutive 99 gait cycles. Since the aim of this study was to identify relationship between the elements, for spatial normalization across participants, all data were subtracted by each minimum value and then divided by maximum value. After the spatial normalization, all of the EMG data were ranged from 0 to 1. In case of inter-module combination, the elements were configured as the sum of agonist muscle activities composing each module. Thus, spatial normalization was conducted again after finding the motor module. All signals were time-normalized to 9900 data points indicating 100 points × 99 gait cycles.

To identify the motor module in EMG activities, we conducted non-negative matrix factorization[19]. Using this linear decomposition technique, we extracted the motor modules from original EMG data (EMGo) as follows: where n is the number of modules, i is individual modules, C is a muscle (m) × i matrix that present muscle weighting indicating the contribution level of individual muscles per each motor module, W is a i × time (t) matrix that module activation profile, and e is residual error. EMGr is reconstructed EMG that is an m × t matrix resulting from the multiplication of W and C. Since low difference between EMGo and EMGr increase the validity of the synergy module, to reduce the residual error, the number of times to repeat the factorization using random initialization for W and H was set at 1500 times of repetitions with 200 times of maximum iteration, and then the result with the lowest residual error was selected. In this study, the number of module was fixed at four by evidence that the motor module in walking is four[20]. To identify the validity of the four modules, we calculated the variability accounted for (VAF) as follows: Theoretically, more complex and various patterns in EMGo results in decreased VAF and increased minimum module number than simple pattern.

Because principle component analysis (PCA) was conducted in the previous study asserting flexible module[18], we also performed PCA using the same dataset with NMF. In both techniques, the modules were deemed the acceptable quality of reconstruction when similarity between original and reconstruction data was higher than 90%. After the analysis of EMG decomposition, to select the agonist muscles of each muscle weighting, one-way analysis of variance (ANOVA) and Dunncan's post hoc analysis was conducted. If significantly difference was identified within the muscle weighing, we chose the muscles having significant high coefficient value and defined it as the agonist of module.

2.4 Data analysis

In the current study, we analyzed covariation between element in both actual and mean-corrected spaces[Fig. 1]. The actual space emphasized covariation of muscle activity related to actual work amount. All measured dataset were divided into each cycle to identify whether covariation values changed between gait cycles. The combinations of elements to compute inter-covariation were listed in [Table 1]. To identify covariation in the actual space, the analysis was modified from previous study[21]. First, time profiles of individual elements [Ei(t)] and of the sum of the individual elements [Etot(t) = Ei(t)] were arranged per each gait cycle. Then, the variance of Ei(t) and Etot(t) were calculated per each gait cycle [VarEi(c) and VarEtot(c) respectively]. Further, the sum of the variances of individual elements [VarEi(c)]

was calculated. Then, the ratio between the two variance values [Var_ratio(c) = VarEtot(c) / ΣVarEi(c)] were divided by the number of elements as a convariation index [Cov_i(c) = Var_ratio(c) / n]. Since covariation values were ranged from 0 to 1 in the results, we subtracted 0.5 from Cov_i(c) value, which indicates the predominance of positive or negative covariation based on zero. In case of Cov_i(c) > 0, positive covariations dominate leading to the positive compensatory synergy between elements. In Cov_ind(c) < 0, it means that negative covariations dominate leading to the negative compensatory synergy between the individual elements. By this calculation, maximum negative and positive covariation values were ranged from -0.5 to 0.5.

Table 1. The combinations of elements to compute inter-covariation

Combination index (n = 17)	Element description
All muscles	All muscle combination
Within-module (Module 1, 2, 3, and 4)	The agonist muscles within each motor module 1, 2, 3, and 4
Agonist-antagonist (TA-MG & RF-MH, each side)	Muscle pair activated toward reverse direction in the same joint
Inter-module	Sum of agonist muscles composing each module

The elements were projected mean-corrected space to demonstrate the relationship between the elements in process of inter-muscle activation. This analysis was especially focused whether the positive covariation was formed with reverse relationship between elements. First, each element in combinations was subtracted from its mean values. Thus, the relationship between the elements has the reverse pattern each other. At this space, the combinations having strong reverse relationship produce relatively high variance while weak reverse relationship results in low variance. Hence, we calculated the mean of the variances in each combination and compared each other. All results were expressed as relatively high or low variance.

All data were described as mean ± standard deviation (SD). To identify significant differences in the covariation and mean variance values between the combination indexes, two-way repeated measures ANOVA (10 combination indexes × 99 cycles) and Dunncan's post hoc were conducted. Specifically, to identify changes of measured values between the gait cycles per each combination, one-way repeated measures ANOVA was performed additionally. Shapiro-Wilk test examined normal distribution of participants' anthropocentric characteristics such as age, weight, and height. Significance for all tests was set at $\alpha = 0.05$. The statistical analysis was conducted using SPSS 19.0 (IBM SPSS Statistics, Chicago, IL, USA).

Ⅲ. RESULTS

Shapiro-Wilk test indicated that anthropocentric characteristics of our participants such as age, weight, and height were normal distribution ($p > 0.05$).

3.1 Motor module for walking

In NMF, all participants showed 4 modules and VAF was 92% ± 1 in the study. The four modules in normal controls were arranged in time order within the gait cycle.

The right RF and TA were agonist muscles in Module 1. This module was activated with major and minor peak phases. The one-way ANOVA and post hoc analysis showed that RF and TA in the right side significantly contributed to produce the module 1 compared to other muscles. The weighting

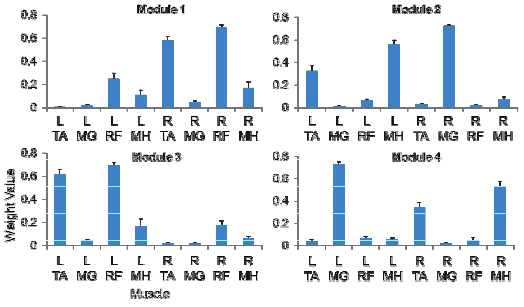

Fig. 2. Muscle weighting values of motor module 1, 2, 3, and 4

coefficients of the right RF and TA were 0.60 ± 0.18 and 0.67 ± 0.16 in the module 1. In module activation profile, the module 1 was activated with major and minor peak phases. The major activation of the module 1 occurred during loading response (-10 ~ 20% of gait cycle) and the minor one was generated during initial swing (60 ~ 80% of gait cycle) in the right leg.

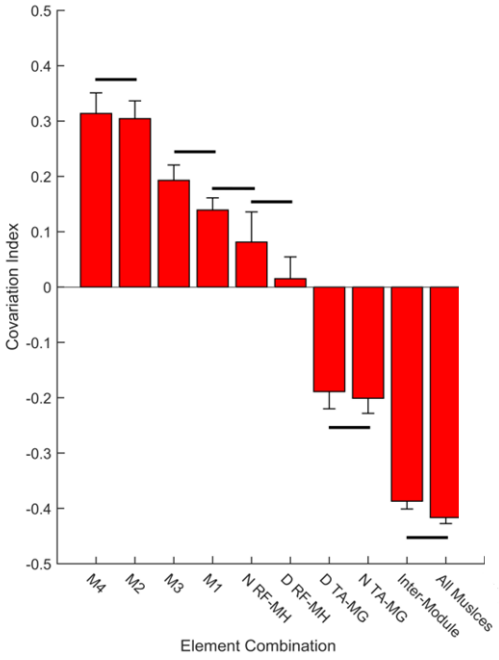

Fig. 3. Comparisons of covariation values

The right MG and left MH were agonist muscles in Module 2. This module mainly consisted of MG in the right side and MH in the left side. The weighting coefficients of these muscles were 0.69 ± 0.08 and 0.57 ± 0.18, respectively. Module 2 was activated with one phase. The activation of the module 1 occurred when the right leg was terminal stance (10 ~ 60% of gait cycle) and the left leg was terminal swing.

The left RF and TA were agonist muscles in Module 3. This module showed symmetrically reversed patterns compared to the module 1. The module 3 mainly consisted of RF and TA in the left side. The weighting coefficients of the left RF and TA were 0.73 ± 0.12 and 0.51 ± 0.13, respectively. In module activation profile, the major activation occurred during loading response (40 ~ 70% of gait cycle) and the minor one was during initial swing (10 ~ 30% of gait cycle) in the left leg.

The left MG and right MH were agonist muscles in Module 4. This module showed symmetrically reversed patterns compared to the module 2. The module 4 mainly consisted of MG in the left side and MH in the right sides. The weighting coefficients of these muscles were 0.68 ± 0.09 and 0.56 ± 0.16, respectively. In module activation profile, the activation occurred when the right leg was terminal swing (60 ~ 110% of gait cycle) and the left leg was terminal stance.

In PCA, eight participants showed 3 modules and one participant was 4 modules. For the eight participants, we conducted the one-way ANOVA to find agonist muscles in each module, but there were no significant different weighting coefficients in PCA module ($p > 0.05$).

3.2 Comparisons in work space

The two-way ANOVA showed significant differences between combination indexes and

Dunncan's post hoc presented seven subgroups that is significant different each other[Fig. 3]. All muscles combinations commonly showed the lowest covariations than other individual combinations ($p < 0.05$).

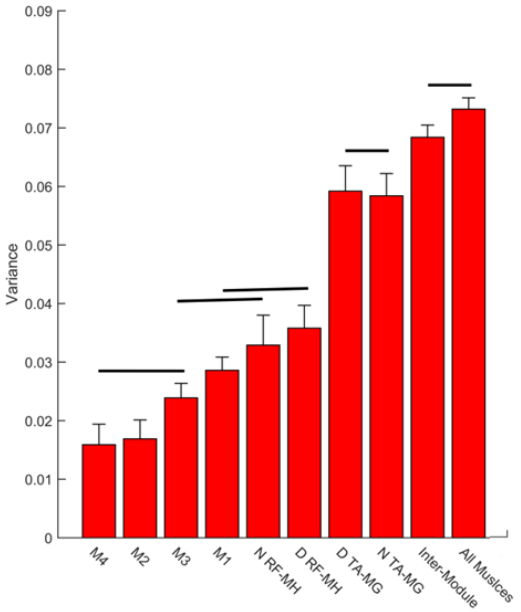

Fig. 4. Mean variance of each combination in mean-corrected space

Positive covariations were showed in the muscle pairs composing the motor module. Among the within-module combinations, the module 2 and 4 showed more positive covariations than module 1 and 3 ($p < 0.05$). When the agonist-antagonist muscles were combined, we found the positive covariation at RF-MH pairs, but the covariation level was low. Although TA-MG pair is also categorized into the agonist-antagonist co-contraction element, it showed negative covariation with significant difference in other combinations ($p < 0.05$). The combination of inter-module and all-muscles presented the highest negative covariation in EMG data ($p < 0.05$), and the two combinations were not significantly different.

3.3 Comparison in mean-corrected space

The results were especially focused in the combination having the positive covariation in the work space. Hence, we specifically observed whether the rank among the combinations was change between the work and mean-corrected spaces, especially in within-module, RF-MH pairs, and cross (D-Knee-N-Ankle, N-Knee-D-Ankle) combinations. The statistical analysis of the variance in the mean-corrected space showed similar results with the work space[Fig. 4]. The rank of variance values was approximately equal to the work space. Thus, our results indicated that there is no positive covariation accompanying the strong reverse relationship between the elements. All muscles and inter-module combinations had higher variance than individual combinations ($p < 0.05$). All within-module combinations showed weak reverse relationship among the all variables ($p < 0.05$).

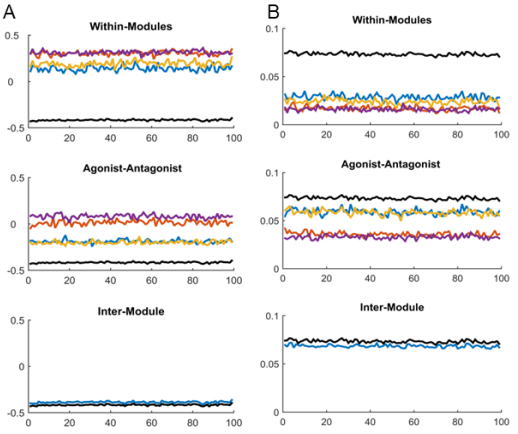

Fig. 5. Time profile of covariation values in work space (A) and mean-corrected space (B)

3.4 Time profiles of compensatory synergies

In covariation of EMG variables, the positive and negative compensatory synergies were continuously

maintained[Fig. 5A]. All covariation values were stable without incline or decline during the task ($p > 0.05$). High deviations were relatively presented in the within-module and the agonist-antagonist combinations, but the deviations were reduced in inter-module and all muscles combinations. Time profiles more clearly showed that RF-MH combination was placed in weak covariation relationship. In case of mean-corrected space[Fig. 5B], the mean variance of combinations also showed stable values per each gait cycle ($p > 0.05$).

IV. DISCUSSION

This study aimed to identify whether a muscle group composing motor module generate positive covariation during walking. As the results, EMG elements showed that the within-module combinations produced the positive covariation, but inter-module combination had negative covariation. The agonist-antagonist muscle pair did not belong to the within-module combination and showed weak positive or negative covariation compared to other combinations. In current study, we could not observe remarkable reverse relationship of the positive covariation identified in mean-corrected space.

As shown in the positive covariation of the within-module combination, specific muscles composing the motor module produced similar temporospatial activities to accomplish task purpose. Less reverse relationship of within-module combination in the mean-corrected space supports that they would be activated together with less inter-communication under hierarchical neural system. Although the agonist-antagonist co-activation of proximal segments showed positive covariation, reciprocal inhibition of interneurons seems to block this covariation pattern. Thus, we presume that the neural mechanism of the co-activation of within-module combination would be different to the agonist-antagonist combinations. Considering that corticospinal axons are connected over several spinal segments with terminal arbors[22], in process of descending motor command, cortical signals would be spread out to several spinal motor neuron pools activating multiple-muscles. This divergent properties were also demonstrated by intra-axonal staining, serial-section, and three-dimensional reconstruction of their axonal trajectories[23]. This study provides evidence that single cortical motor neurons innervate a functional set of multiple muscles. The multi-connection in neural system implicates the neural implementation of the motor module to reduce redundant control system. Hence, there is high probability that human central nervous system habitually uses a combination of muscle elements generating muscle forces across several joints during walking.

In contrast to the within-module combination, the inter-module had obvious negative covariation. Moreover, the deviation of covariation values was quite low in the inter-module. That is, the positive covariations of the within-modules would construct stable negative covariation of the inter-module. Moreover, the inter-module showed stable negative covariation. Thus, as the sum of each joint movement is much more stable than the individual joint by compensatory synergies[5], each motor module may correspond to individual joint having strong negative compensatory synergy for motor-equivalent covariation[24]. If so, motor module would be a basic control unit in muscular system.

To identify the motor modules, we conducted two decomposition techniques, NMF and PCA. The decomposition technique has great advance to

simplify large and complicate EMG data measured in various muscles under high sampling rate. In addition, since the results of simplified EMG data are quantitated based on the muscle weighing and the module activation profile, these results would be more utilizable to understand human movement mechanism than an intuitive interpretation of individual EMG data.

The notion of EMG decomposition has been disagreed according to whether the muscle weighing is fixed or varied[16]. Interestingly, in process of EMG decomposition, PCA was used in the studies asserting the varied muscle weighting corresponding to m-modes[17][18], while NMF was in the fixed muscle weighting as the muscle synergy[16][25]. In current study, we used the decomposition techniques only to identify the motor modules in bilateral low extremity muscles during walking because the intervention of decomposition process might disturb presenting underlying nature of motor output coordination. Furthermore, we used both decomposition techniques to choose the agonist muscles of the module because different results could arise by different technique[26]. Then, the covariation values of muscle activities were calculated using original dataset. As the result, we failed to choose the agonist muscles of the module in PCA because there was no significant high value in muscle weighting coefficients extracted from PCA. These results might support the notion of M-mode asserting the varied muscle weighting. If muscle weighting coefficients were varied per each gait cycle, the covariation values of each EMG combination would be various between the gait cycles. However, no significant difference between the gait cycles would support the notion of the fixed muscle weighting. Hence, we chose the muscle pairs within-module based on NMF results and focused variability of covariation values. As shown in [Fig. 5], the covariation in the inter-module combination present very stable values during whole gait cycles. In addition, the all combination indexes resulted in no significant difference between each gait cycles. It means that human walking has fixed muscle weighting that maintains relationship of each muscle pair without various pattern changes. Thus, this study more supports the results of NMF than those of PCA.

The different results of PCA might be caused by the characteristics of the technique. Considering that PCA results in negative number even though muscles generate no negative activities, non-negative technique would be more reliable than orthogonal methods like PCA in composition of inherently positive quantified variables[26][27]. In practice, the agonist muscles of each module extracted from NMF were biomechanically interpretable well. However, the result on PCA had to confront explaining why irregular muscle weighting patterns containing negative values are produced in walk steady treadmill walking. These facts indicate that usage of PCA in EMG data seems to be open to doubt in terms of biomechanical interpretation of the results.

In conclusion, it has been believed that human brain concentrates particular variables related to task performance. To conduct desired task, multi-segment coordination are accompanied with multi-muscle activations innervated by the central nervous system. To identify complex motor output patterns, we identified covariation patterns of muscular elements. As the results, we found that specific muscle groups composing the within-modules produce the positive covariations. Further, less interaction within the muscle group was identified in mean-corrected space in contrast to between the groups. Hence, we presume that muscular elements have unique physiological characteristic that forms the control unit

within the elements. Stable negative covariation of the inter-module also suggests that the motor modules may be the control unit in the complex motor coordination. We expect that covariation mechanism during walking would be contributable to data science and digital health care[27][28].

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저 자 소 개

김 유 신(Yushin Kim) 정회원

- 2014년 2월 : 고려대학교 물리치료학과(이학박사)
- 2016년 3월 ~ 현재 : 한국과학기술원 신경재활공학연구실 연구원

<관심분야> : 운동조절, 재활과학

홍 영 기(Youngki Hong) 정회원

- 2011년 7월 : 고려대학교 의학과(의학박사)
- 2013년 3월 ~ 현재 : 청주대학교 스포츠의학과 조교수

<관심분야> : 척추수술, 재활과학