Exploring Corticomuscular Coupling During Active and Passive Movements using Electroencephalography and Surface Electromyography

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Exploring corticomuscular coupling during active and passive movements using electroencephalography and surface electromyography

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Abstract

Purpose The rehabilitation training of stroke patients based on their movement intentions can improve their chances of recovery because movement intention affords greater integration of the brain and muscle functions during training. Against this backdrop, in this study, we acquired the electroencephalography (EEG) and surface electromyography (sEMG) data related to the grasping movements of 14 healthy subjects in the active- and passive-movement modes to explore corticomuscular coupling in these modes.

Methods Transfer entropy (TE) was calculated between EEG and EMG signals in different frequency bands. We also calculated the power spectral density (PSD) of EEG signals. In order to study the transmission of information between different brain regions, we also constructed a corticomuscular network (CMN), and calculated various network metrics using graph theory.

Results The power spectral density of active movement in the beta band was significantly greater than that of passive movement, and the spectral power ratio of the beta and alpha bands also increases. TE value of active movement was significantly higher than that of passive movement. The corticomuscular network metrics between these two movement modes were different.

Conclusion Movement intention has a great influence on human movement. Active movement enhances the information interaction between brain regions and muscles, and higher information-transmission efficiency.

Keywords: electroencephalography, surface electromyography, corticomuscular coupling, transfer entropy, corticomuscular network
1 Introduction

Stroke is currently one of the leading causes of death and disability in the global population. In addition, nearly 75% of stroke survivors suffer from different degrees of dysfunction. The rehabilitation training of stroke patients plays an important role in the recovery of their movement function. Stroke is a disorder of brain nerve function caused by cerebrovascular dysfunction, which affects body movement and language function. Severe stroke can cause physical, speech, and sensory dysfunctions. However, stroke patients can develop compensatory behavior strategies to perform daily activities in the event of loss of function [1]. Moreover, stroke patients can be taught to reconstruct the damaged brain through rehabilitation training to recover and compensate for the damaged or lost functions.

Rehabilitation treatment in the early stage of stroke can significantly aid the recovery of brain function and the degree of nerve remodeling because such treatment can strengthen the reorganization of the cortex and promote relearning of the damaged brain [2, 3]. To improve the effects of rehabilitation, stroke patients should ideally undergo timely rehabilitation training after their condition is stabilized.

Rehabilitation training includes both active and passive training. In this context, there is evidence that passive movement is insufficient to afford movement recovery [4]. Meanwhile, rehabilitation training based on the patient movement intention (i.e., active training) can improve the rehabilitation effects [5], and thus stroke patients are encouraged to actively exercise.

In recent years, newly developed brain–computer interface (BCI) technologies have been used to identify patient movement intention to promote their participation in rehabilitation training and enhance the rehabilitation effects. In this context, several studies have focused on motion-intention recognition and classification, and in particular, studies based on the combination of inverse electroencephalography (EEG) and common spatial patterns [6] have yielded satisfactory results. In general, the BCI system uses EEG signals to recognize user intention; however, the system accuracy is relatively low [7]. Meanwhile, the fusion of EEG and electromyography (EMG) signals reportedly improves the reliability of the BCI system [8]. When the patient is able to actually perform an exercise, the brain regions related to movement form connections [9], and there is a functional integration of the brain and muscles [10].

During exercise, in addition to the synergy between different brain regions, the related brain regions and muscle tissues also interact, which is called corticomuscular coupling (CMC) [11, 12]. Coherent activity between the movement cortex and muscles is considered to reflect the synchronous firing of cortical spinal cells [13], and it can be estimated by analyzing the frequency
coherence between EEG and EMG signals (EEG–EMG coherence). CMC has attracted significant interest, and several studies have focused on different movement intentions to analyze the difference in the CMC during active and passive movements.

Many studies have shown that the intensity of EEG–EMG coherence during active movement is significantly higher than that during passive exercise [14]; however, there has been no quantitative analysis of the force induced in the muscles of interest during active and passive movements considering that the force magnitude can affect the frequency range of EEG–EMG coherence [15]. To the best of our knowledge, there are currently few studies on the effects of movement intention on the integration of brain and muscle functions and the application of the corticomuscular network (CMN) for analysis. In addition, the traditional coherence-analysis method cannot effectively analyze the EEG–EMG coherence direction and nonlinear coupling characteristics during movement. Meanwhile, the coupling relationship as measured by the coherence method includes direct and indirect effects, which can lead to overestimation of the coupling strength [16]. In this regard, transfer entropy (TE) can be used to explore the nonlinear coupling characteristics between neural signals and to clarify the directional relationship between the variables of interest.

In this paper, we propose, for the first time, the use of TE in conjunction with graph theory to construct a CMN. We explore the influence of movement intention on the integration of brain and muscle functions during upper-limb movements.

2 Materials and methods

The study subjects included 14 healthy right-handed young adults (9 men and 5 women aged between 23 and 26). The research purpose and detailed experimental procedure were clearly explained to them before the start of the experiment. Potential subjects with a history of musculoskeletal or neurological diseases or those taking interfering drugs were excluded. Prior to the start of the study, all subjects provided written informed consent. The local ethics committee approved all the trial procedures.

The G.MOBIIlab MP-2015 wireless EEG system was used to record EEG signals at 15 scalp sites (Fz, F3, F4, F7, F8, Cz, C3, C4, T7, T8, Pz, P3, P4, P7, P8) at a sampling frequency of 1000 Hz. The electrodes were positioned according to the international 10–20 system. Simultaneously, sEMG signals were recorded by using a Trigno Wireless EMG acquisition instrument with a sampling frequency of 1926 Hz. Four EMG electrodes were used to acquire sEMG signals from the flexor digitorum superficialis (FDS), extensor digitorum (ED), flexor carpi ulnaris (FCU), and extensor carpi radialis brevis (ECRB). Before signal acquisition, the relevant skin areas were wiped
with alcohol to remove oil and dander from the skin surface.

The rehabilitation device used in our experiment was an improved rehabilitation training device that can assist subjects in grasping within a certain range. The device actuator was equipped with a pressure sensor and a button to adjust the applied force. The actuator was placed on the mechanical device, and which was placed on four fingers (excluding the thumb) of the participants. To avoid discomfort and possible injury caused by excessive pressure, the actuator was padded with a soft buffer material.

2.1 Overview

Fig. 1 provides an overview of the study. After preprocessing the synchronously acquired EEG and sEMG signals, we calculated the power spectral density (PSD) of the EEG signals for different frequency bands. Subsequently, we calculated the TE values corresponding to active and passive movements and constructed the CMN. The graph-theory method was used to analyze the CMN.

2.2 Experimental design

The signal-acquisition experiments were performed on the subjects in an electrically shielded room to reduce electronic interference. Fig. 2 shows the process of the synchronous acquisition of
EEG and sEMG signals. Before the experiment, the subjects were asked to rest for 5 min to ensure that their bodies were relaxed.

Fig. 3 shows an image of the signal-acquisition process. In the experiment, to prevent the subjects from anticipating the start of each trial, they were asked to wait for 10 s before gripping a strength meter. In the active-movement-mode trials, the subjects were asked to view the screen. On hearing a beep sound and watching a cross appear on the screen, the subjects grasped the 10-kg grip strength meter within 2 s and maintained the grip for 5 s. A visual cue on the screen prompted the end of the trial, and subsequently the subjects were allowed to relax their hand for 5 s. In the passive-movement-mode trials, the subjects smoothly placed their hand on the device; no gripping was required. Upon hearing a beep and viewing the cross on the screen, the subjects placed their hand on the meter. The grip strength value was increased to 10 kg within 2 s and then maintained at this value for 5 s. A visual cue on the screen prompted the end of the trial, and subsequently the subjects relaxed their hand. Each subject rested for 30 s after each trial, and 20 trials were conducted for each mode.

Fig. 2 Electroencephalography (EEG) and surface electromyography (sEMG) signal-acquisition experiments.
2.3 Data processing and analysis

2.3.1 Data preprocessing

Data preprocessing included the following steps: first, data with large artifacts were eliminated, and the corresponding signals were discarded. Because EEG and sEMG signals are weak and susceptible to interference from noise and power frequency, we used an adaptive filter to remove the 50-Hz power signal. Subsequently, we applied independent component analysis to remove ECG and electrooculography (EOG) signals and wavelet denoising to the EEG signal. The sEMG signal was downsampled at the same frequency as the EEG signal. Empirical mode decomposition (EMD) and wavelet threshold were combined to remove the noise signal in EMG. Through band-pass filtering, the basic EEG rhythms were divided into the δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–32 Hz), and γ bands (32–45 Hz).

2.3.2 Quantitative EEG parameters

The PSD of each channel was calculated by Welch’s periodogram, and the PSDs of all tests were averaged. Under the presence of actual exercise, the cognitive activity of the brain will produce alpha (8–13 Hz) and beta waves (13–32 Hz) [17]. Therefore, the absolute power was summed in the alpha (8–13 Hz) and beta (13–32 Hz) frequency bands. The relative power value of each frequency band was calculated as the ratio of the summed absolute band power and the total power in the range of 0.5–45 Hz.

The absolute band power was used to calculate the Beta/Alpha ratio (BAR). The BAR is defined as the ratio of the spectral power of the beta and alpha bands as follows:
\[
BAR_c = \frac{\langle P_c(f) \rangle_{f=13\ldots32Hz}}{\langle P_c(f) \rangle_{f=8\ldots13Hz}}
\]

\(P_c(f)\) was determined as the mean of the band power. Then, we averaged the ratio of each EEG channel to obtain the BAR:

\[
BAR = \frac{1}{N} \sum_{c=1}^{N} BAR_c
\]

### 2.3.3 Transfer-entropy analysis

Schreiber proposed a TE method based on information theory to quantify the information transfer between variables [18]. We note here that TE is a nonlinear extension of Granger causality [19].

Parameter TE quantifies the amount of information transferred from one process \(X\) to another process \(Y\), where \(X = \{x_1, x_2, \ldots, x_N\}\) and \(Y = \{y_1, y_2, \ldots, y_N\}\). Here, \(N\) denotes the length of the time series. The TE from \(X\) to \(Y\) can be expressed as per the following formula:

\[
TE_{x\to y} = \sum_{n=1}^{N} p(y_{n+\tau}, x_n, y_n) \log_2 \left( \frac{p(y_{n+\tau}, x_n, y_n)}{p(x_n, y_n) p(y_{n+\tau}, y_n)} \right)
\]

Here, \(n\) denotes the index of discrete time, \(\tau\) the predicted time, and \(p\) the probability distribution. The TE value reflects the coupling strength between the data in this time period.

### 2.3.4 Construction and analysis of corticomuscular network

The CMN based on the EEG and EMG signals can be constructed in three steps. First, we calculated the signal TE to obtain a \(19 \times 19\) adjacency matrix. Next, we binarized the original adjacency matrix to form a binary adjacency matrix composed of only 0s and 1s. Here, for TE values greater than the threshold value \(TH\), the corresponding element of the matrix was set to 1; otherwise, it was set to 0. The selection of the threshold affects the structure of the corticomuscular network, and therefore it is very important to choose a suitable threshold for binarization. In this study, the significance-level method was used to calculate threshold \(TH\). The threshold calculation formula can be expressed as follows:

\[
TH = 1 - (1 - \hat{\partial})^{1/(L-1)}
\]

Here, \(L\) denotes the length of the data and \(\hat{\partial}\) the degree of significance, which was set to 0.95. Finally, we calculated and analyzed the network characteristics, including the out-degree, in-degree,
average clustering coefficient, and local efficiency.

2.3.5 Graph analysis

The following network metrics were used to analyze the binary adjacency matrix:

1) Node degree

The node degree is a basic and important measure in a network. In the directed graph, the degree of nodes is the sum of the in- and out-degrees [20]. The out-degree, in-degree, and degree of node $i$ can be calculated by using the following formulas:

$$D_{i}^{out} = \sum a_{ij}$$  \hspace{1cm} (5)  

$$D_{i}^{in} = \sum a_{ji}$$  \hspace{1cm} (6)  

$$K_{i} = D_{i}^{out} + D_{i}^{in} = \sum_{j \in N_{i}, i \neq j} a_{ij}$$  \hspace{1cm} (7)  

2) Local efficiency

Local efficiency is used to represent the ability to process and transmit local information [21]. The local efficiency of node $i$ can be calculated as follows:

$$E_{i,local} = \frac{1}{n_{i}(n_{i} - 1)} \sum_{i \neq j, i \in N_{i}} \frac{1}{l_{ij}}$$  \hspace{1cm} (8)  

where $N_{i}$ represents the set of nodes directly connected to node $i$, $n_{i}$ is the total number of nodes in set $N_{i}$, and $l_{ij}$ is the shortest path length between nodes $i$ and $j$.

3) Clustering coefficient

The clustering coefficient represents the degree of clustering of similar nodes in the graph and describes the possibility that individual neighbor nodes in the network are also neighbors. In a network, node $i$ has $k_{i}$ connecting edges to other nodes, and node $k_{i}$ is the neighbor of node $i$. The clustering coefficient of the nodes can be defined as

$$C_{i} = \frac{2E_{i}}{k_{i}(k_{i} - 1)}$$  \hspace{1cm} (9)  

where $E_{i}$ refers to the number of edges actually present at node $i$.

2.4 Statistical analysis

All statistical tests were performed using SPSS version 22.0. Paired sample t-tests were used to obtain statistical differences in the TE, PSD, and network metrics for two movement modes. We
set the level of significance at p<0.05, and Bonferroni’s correction was applied to correct for multiple comparisons.

3 Results

3.1 Quantitative EEG parameters analysis

Fig. 4 shows the PSD distributions of the subjects for alpha and beta bands in the two movement modes. The paired sample t-tests were used to identify significant differences between the two states. The results show that the PSD within the alpha band did not exhibit a significant difference (p=0.07), but there was a significant difference in the beta band (p=0.0024). Here, we note that different EEG frequency bands are correlated with different physiological functions of the brain [22]. In the alpha band, the PSD of the prefrontal lobe was higher than that in other areas. In the beta band, the PSD of active movement was significantly higher than that of passive movement. Fig. 5 shows the power ratio of the beta band and the alpha band of the two movement modes. The statistical results show that for the passive mode, the BAR of the active mode significantly improved (p=0.0025). Compared with the passive mode, the active mode had a larger BAR.

Fig. 4 Power-spectral-density distributions of alpha and beta bands for the two movement modes.
3.2 Transfer-entropy analysis

In this study, TE was used to calculate the strength of CMC. To determine the significance of the difference between the active and passive movements according to different frequency bands, the paired sample t-test was used for the statistical analysis of the TE results. Fig. 6 shows the average TE value for different frequency bands in the active- and passive-movement modes. The results of the statistical analysis can be seen in Table 1. Compared with passive movement, except for the δ band, the TE value significantly increased in the active movement. In addition, the value of CMC in the beta band was significantly larger than other frequency bands. The EEG–EMG and EMG–EEG directions exhibited the same trend. Therefore, it was evident that CMC mainly occurred in the beta band, and we selected the beta frequency band for further analysis.

![Graph showing power ratio of the beta and alpha bands of the two movement modes.](image)

**Fig. 5** Power ratio of the beta and alpha bands of the two movement modes.
Fig. 6 Average transfer entropies for different frequency bands in the active- and passive-movement modes.

(A) Transfer entropy according to active- and passive-movement modes in EEG->EMG. (B) Transfer entropy according to active- and passive-movement modes in EMG->EEG.

Table 1
Descriptive statistics and outcomes of paired sample t-tests of transfer entropy in active- and passive-movement modes.

| EEG bands | active |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
|-----------|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
|           | EEG->EMG | EMG->EEG |     |     | p1  | p2  | EEG->EMG | EMG->EEG |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| δ         | 0.044   | 0.0058 | 0.036 | 0.0033 | 0.4  | 0.34 | 0.045   | 0.0025 | 0.037 | 0.0043 |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| θ         | 0.082   | 0.028  | 0.076 | 0.029  | 0.0035 | <0.001 | 0.058   | 0.012  | 0.054 | 0.001  |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| α         | 0.14    | 0.032  | 0.133 | 0.026  | <0.001 | <0.001 | 0.08    | 0.0047 | 0.082 | 0.0053 |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| β         | 0.329   | 0.029  | 0.31  | 0.064  | <0.001 | 0.005  | 0.2766  | 0.038  | 0.3    | 0.073  |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| γ         | 0.215   | 0.016  | 0.2   | 0.059  | <0.001 | <0.001 | 0.146   | 0.022  | 0.1735 | 0.01   |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
Mean: average value; SD: standard deviation; p1: the p value of the two modes in EEG->EMG; p2: the p value of the two modes in EMG->EEG.

3.3 Corticomuscular network

By calculating the TE values of the 15-channel-lead EEG signals and four muscle sEMG signals, we constructed the average effective adjacency matrix for the β bands of the two movement modes. Fig. 7 shows the average adjacency matrix and corticomuscular networks in the two movement modes. The paired sample t-test was used to determine the significance of the difference between active and passive exercise. We found that the overall functional connectivity strength during active movement was significantly enhanced when compared with that for passive movement (p<0.001). The number of CMN connecting edges and the CMN complexity increased significantly, and the number of connections between brain regions greatly increased (p=0.003).

Fig. 7 Average adjacency matrices and corticomuscular networks (CMNs) corresponding to β bands in the two movement modes. (A) Average adjacency matrices and CMNs in active movement. (B) Average adjacency
matrices and CMNs in passive movement.

### 3.4 Network characteristics

![Graphs showing network characteristics](image)

**Fig. 8** Average network characteristics in the beta band for active- and passive-movement modes. (A) Average degree (in-degree and out-degree). (B) Average clustering coefficient. (C) Average local efficiency. For all graphs, the red line represents the active-movement mode, and the black line represents passive-movement mode; *p<0.05.
Fig. 8 shows the average network degree, clustering coefficient, and local efficiency for the beta frequency bands in both the active- and passive-movement modes. There are significant differences between the two modes.

The individual degree values reflect the importance of nodes in the network, with larger degrees indicating regions more susceptible to connections with other regions and a greater number of functional goals. As shown in Fig. 8A, the in-degree and out-degree values for active movement were greater than those for passive movement, which indicates that the corticospinal correlation is higher during active movement than during passive movement. We note that for the two movement modes, the C3 electrode exhibited the higher in-degree and out-degree than those for C4. This result may be correlated with the right-handedness of the selected subjects, and it also verifies the contralateral control mechanism of the brain [23]. The paired sample t-test was performed on the out-degree and in-degree of all nodes in the two groups; a significant difference was observed between the groups (in-degree: p<0.001; out-degree: p=0.012).

The clustering coefficient is used to describe the clustering degree of the vertices in a graph. The clustering coefficient of a single node represents the degree of connection between the neighbors of the node. Fig. 8B shows the average clustering coefficients of each node for the beta band in the two movement modes. The clustering coefficients of all nodes in the two groups were determined using the paired sample t-test. The results indicated that, for passive movement, the clustering coefficient of active motion increased significantly (p=0.002). Thus, active movement with intention may confer greater ability to complete upper-limb movements.

The local efficiency represents the local-information-transmission ability of the network. Through statistical analysis, it was found that there was a significant difference between the two groups (p<0.001). The local efficiency of active movement was higher than that of passive movement. In other words, movement intention affects the efficiency of information transmission between the brain regions and muscles, and the ability to process and transmit information between the brain and muscles is greater in the active-movement case.

4 Discussion

In this study, we quantitatively analyzed multi-channel EEG signals and the EMG signals of related muscles to explore the influence of movement intention on the integration of brain and muscle functions during upper-limb movement. We calculated the PSD of the EEG in the two modes and the power ratio between the beta and alpha bands to compare their frequency-domain energy distributions in different frequency bands. We used graph theory and TE to construct the
CMN corresponding to beta bands in the active- and passive-movement modes. We analyzed the network using the three metrics, i.e., degree, local efficiency, and clustering coefficient, and we explored the CMC corresponding to active and passive movements.

The activity of the cortex is affected by muscle strength. The activation of the primary and secondary motor areas is linearly related to a certain force generation [24], and there is a different relationship between the multiple oscillations of the cerebral cortex and the force [25]. Therefore, in this study, we controlled the force of the two modes to avoid the influence of the strength on the experimental results. When actual exercise is performed, the cognitive activity of the brain will produce alpha (8–13 Hz) and beta waves (13–32 Hz). We calculated the PSD of the EEG signals in the alpha and beta bands for two modes. The results showed that the PSD distributions of the two modes in the alpha band were similar, and the distribution was larger in the prefrontal region. In the beta band, the PSD of active movement was significantly greater than that of passive movement in the prefrontal lobe, motor areas on both sides, and parietal lobe. This may be because the frontal and parietal areas are related to thinking and body perception. The “existence” of movement intention increases the involvement of these brain areas in upper-limb movements. Based on the difference between the two modes in the beta band, we assumed that the beta band is more influential in active movement as compared to that in passive movement, and thus we calculated the BAR value. The BAR of active movement was significantly higher than that of passive movement. Previous studies have proved that higher beta spectral power improves motor performance [26].

In the study, we used TE to calculate the CMC during movement. TE can be used to explore the nonlinear coupling characteristics between neural signals and to characterize the directional relationship between the variables of interest. Our results indicated that CMC mainly occurred in the beta band, in both the active- and passive-movement modes; the TE value in the beta band was the largest. This is consistent with the results of previous studies, which indicated that the oscillating cortical activity of steady-state motor output under static force is related to the synchronization of the beta bands between muscle activities [27, 28]. CMC in the beta band shows task dependence [29]. Furthermore, the magnitude of the force affects the value of the CMC. Here, we controlled the strength of the force and only analyzed the data in the hold phase. The TE value of active movement was significantly greater than that of passive movement, which is consistent with results of previous studies [14]. We believe that the participation of motor intention can enhance the CMC and drive spinal motoneurons more effectively, thereby improving the motor performance.

The CMC mainly occurs in the beta band and is generally considered to be the combination of synchronous cortical activity output in the primary motor area and spinal cord motor output [30]. Previously, networks have rarely been constructed to study the connections between brain and
muscle regions. In this study, we constructed a CMN in the beta band and used graph theory to analyze it. As shown in the CMN diagram in Fig. 7, when compared with the active-movement case, the number of connecting edges of the CMN during passive movement was significantly reduced. In other words, the network complexity was significantly reduced, and the function exhibited a decreasing trend.

Previous studies have suggested that the brain regions activated by passive and active motions are similar [31]. However, we believe that the intensity of activation may be different, and there are differences in the connections between the two motor brain regions and the efficiency of information transmission. Our results indicate that there are obvious differences in network characteristics between the two movement modes. In our analysis of the CMN in the two movement modes, we fully analyzed the characteristics of the effective network based on the degree and its distribution, the clustering coefficient, and the local efficiency. The greater the node degree, the greater the role of the node in information transmission in the network. Our results showed that the out-degree and in-degree of active-movement nodes were larger than those of passive-movement nodes. For active movement, F7, C3, and FCU exhibit higher in-degree and out-degree values; it is possible that area where these nodes are located acts as a network hub.

The clustering coefficient represents the functional separation index of the network. Functional separation refers to the ability to perform special processing in the brain regions. In the center of the primary motor area, the frontal lobe, and the parietal lobe, the aforementioned three metrics were in the case of active movement as compared to passive movement. This indicates that the information-processing ability of these brain regions is weakened in passive movement [32]. In the process of movement, CMC is not solely the combination of synchronous cortical activity output in the primary motor area and spinal cord motor output. In addition to the sensorimotor cortex, the blood flow in the somatosensory motor area also increases during motor activity [33]. Moreover, previous studies have shown that proprioceptive processing is important for proper motion control, providing false feedback and internal representation of motion for adjusting motion commands [34]. Consequently, we can infer that during passive movement, the information interaction between the center of the primary motor area, the frontal lobe, the parietal lobe, and the muscles is degraded, which reduces the ability to control muscles. The local efficiency of nodes in the network also shows a similar result. Local efficiency is normally used to describe the information-exchange efficiency of a local network, and it also reflects the ability of the network to defend against random attacks to a certain extent. The proprioceptive motor during active movement may result in the higher efficiency of the brain in recognizing the corresponding movement instructions and transmitting the information to the muscles.
5 Conclusion

To the best of the authors’ knowledge, this is the first study to combine the cerebral cortex and muscles to build a network to explore the influence of exercise intention. Furthermore, we calculated the PSD in the alpha and beta bands and the BAR values in these bands. For stroke patients, rehabilitation training with movement intention in the early stages of stroke can improve the training effect. In this study, we confirmed the greater interconnectedness of the cortical muscles and greater brain activity during active movement than during passive movement. In our CMN analysis, we found that the CMN corresponding to active movement exhibits greater complexity, and the information interaction between brain areas and muscles is enhanced. Moreover, the brain more efficiently recognizes the corresponding movement instructions and transmits information to muscles. As regards the study limitations, we only considered healthy subjects; no stroke patients were considered. Moreover, the sample size was not sufficiently large. Nevertheless, to the best of our knowledge, few studies have focused on this research area. Thus, studies in this direction can reveal the influence of exercise intention on the integration of brain and muscle functions. Our findings can also be of value for preclinical research.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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