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Emotion-movement relationship: A study using functional brain network and cortico-muscular coupling

Xugang Xi[a,b,*], Qun Tao[a,b], Jingqi Li[c,**], Wanzeng Kong[b,d], Yun-Bo Zhao[e], Huijiao Wang[f], Junhong Wang[a,b]

[a] School of Automation, Hangzhou Dianzi University, Hangzhou 310018, China
[b] Key Laboratory of Brain Machine Collaborative Intelligence of Zhejiang Province, Hangzhou 310018, China
[c] Hangzhou Mingzhou Naokang Rehabilitation Hospital, Hangzhou 311215, China
[d] School of Computer Science and Technology, Hangzhou Dianzi University, Hangzhou, China
[e] Department of Automation, University of Science and Technology of China, Hefei, China
[f] Hangzhou Vocational & Technology College, Hangzhou 310018, China

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ABSTRACT

Background: Emotions play a crucial role in human communication and affect all aspects of human life. However, to date, there have been few studies conducted on how movements under different emotions influence human brain activity and cortico-muscular coupling (CMC).
New methods: In this study, for the first time, electroencephalogram (EEG) and electromyogram physiological electrical signals were used to explore this relationship. We performed frequency domain and nonlinear dynamics analyses on EEG signals and used transfer entropy to explore the CMC associated with the emotion-movement relationship. To study the transmission of information between different brain regions, we also constructed a functional brain network and calculated various network metrics using graph theory.
Results: We found that, compared with a neutral emotional state, movements made during happy and sad emotions had increased CMC strength and EEG power and complexity. The functional brain network metrics of these three emotional states were also different.
Comparison with existing methods: Much of the emotion-movement relationship research has been based on subjective expression and external performance. Our research method, however, focused on the processing of physiological electrical signals, which contain a wealth of information and can objectively reveal the inner mechanisms of the emotion-movement relationship.
Conclusions: Different emotional states can have a significant influence on human movement. This study presents a detailed introduction to brain activity and CMC.

1. Introduction

Emotion, the external manifestation of human physiological and psychological changes, is an important medium for human communication and plays a central role in our daily lives. Different emotions have different effects on human cognition, decision-making, and action (James, 2011; Spence, 1995); therefore, it is important to fully understand the relationships between emotions and human activity. At present, there are many parameters that can be used to measure human emotions (Haag et al., 2004; Chanel et al., 2007), such as the galvanic skin response, which shows changes in skin electrical conduction when stimulated and is generally used as a measure of negative emotions; respiration rate, thought to be related to anger; and heart rate, thought to be associated with negative emotions, such as fear. Human emotions can also be measured using functional magnetic resonance imaging and electroencephalogram (EEG) data (Chanel et al., 2007). It is well known that emotion is the brain's external response to psychological activity and that there is a close connection between emotion and the cerebral cortex. EEG, derived from physiological electrical signals, reflects neuronal activity in the brain. Although the spatial resolution of EEG is

* Corresponding author at: School of Automation, Hangzhou Dianzi University, Hangzhou 310018, China.
** Corresponding author.
E-mail addresses: xixi@hdu.edu.cn (X. Xi), ljingqi@163.com (J. Li).

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not very high, it has a high temporal resolution, signal acquisition is very simple, and it is non-invasive and therefore does not cause any harm to the human body. Hence, it is very useful for measuring emotions (Campbell et al., 2010; Niemic et al., 2002; Ali et al., 2016).

There is a close relationship between emotions and brain activity. Studies have shown that the power of the EEG alpha band is particularly important for studying emotions. Additionally, during emotion regulation, activity in the left and right hemispheres of the brain has been found to be different (Harmon-Jones, 2003). It has been proposed that this asymmetry in the frontal lobe is related to emotion, where positive emotion is associated with left frontal lobe activation, and negative emotion is associated with right frontal lobe activation (Balconi and Mazza, 2010; Waldstein et al., 2000; Wheeler et al., 1993; Davidson and Henriques, 2000). Schmidt et al. also discovered this asymmetry by studying the emotions induced by different types of music and demonstrated that frontal lobe activity gradually decreased in relation to fear, happiness, and sadness (Schmidt and Trainor, 2001). Keil et al. found a significant right-hemispheric preponderance in the gamma frequency bands associated with aversion (Keil et al., 2001). Although these studies have achieved significant results, most of the conclusions are associated only with the frontal lobe of the brain, ignoring the role of the entire brain during changes in emotion. However, the brain has a complex system of neurons in different areas, leading researchers to study the brain functional network. In the current study, a functional brain network was constructed to explore the emotion-movement relationship, and specifically, changes in connections during different emotional states. Network topology properties were used as metrics to determine the differences between the networks.

The relationship between emotions and human behavior is inextricable. Different emotions are thought to trigger specific biases that affect people's behavior. The relationship between human behavior and emotion involves not only the synergy between brain regions, but also the interaction between brain regions and the peripheral nerves of related muscles, also defined as cortico-muscular coupling (CMC) (Cremoux et al., 2017). Transfer entropy is widely used in CMC analysis as a measure of bidirectional transmission between two time series. Gao et al. for instance, found that the coupling strength of electromyogram (EMG)→EEG in the affected side of stroke patients was greater than that of EEG→EMG (Gao et al., 2018).

At present, emotion-focused research has primarily relied on EEG

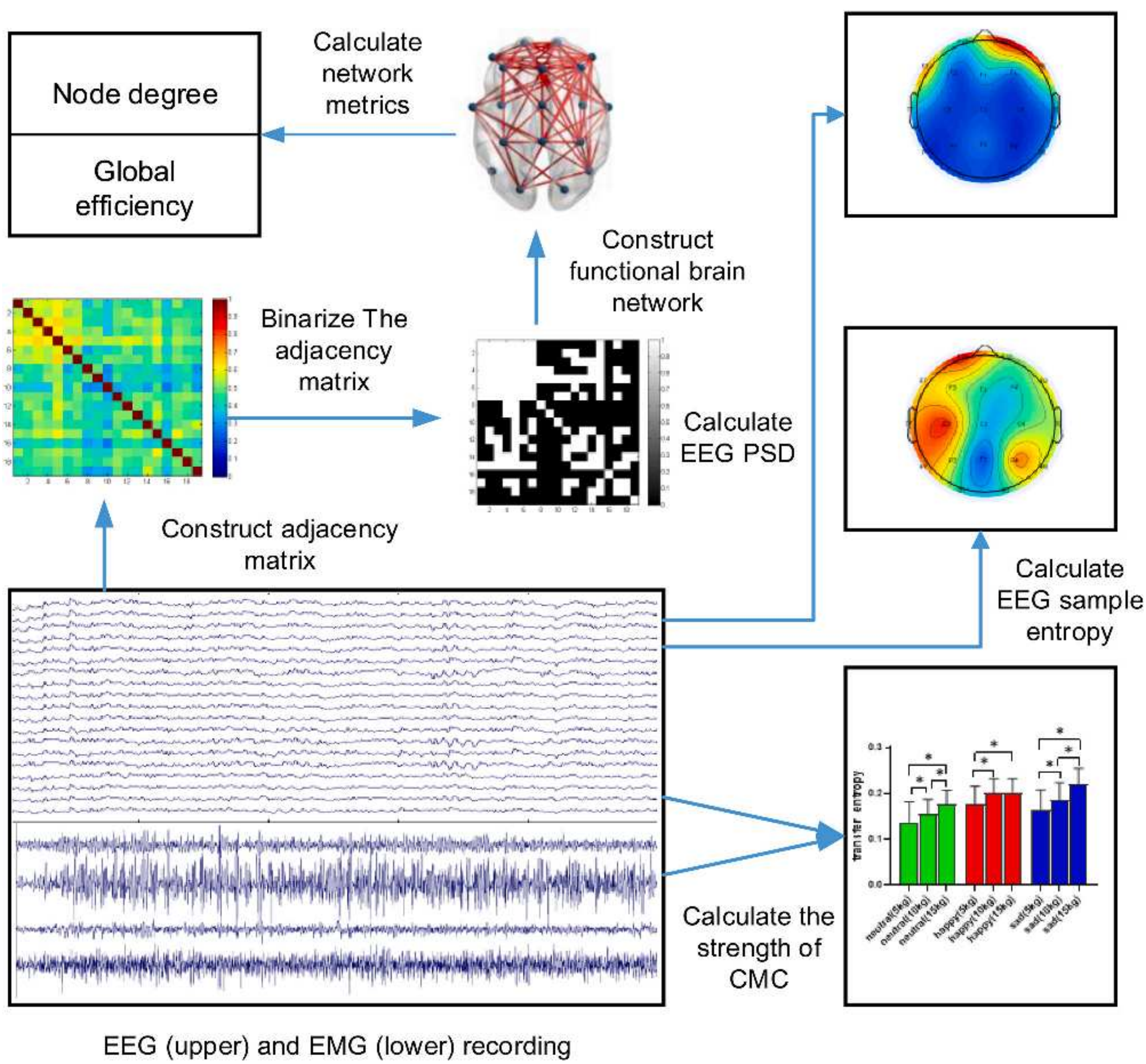

Fig. 1. Data processing workflow.

signals to classify emotions. However, few studies have combined emotions and movement to explore the relationship between them. This study aimed to use physiological electrical signals to determine changes in the cerebral cortex and between the cortex and muscles caused by emotional changes. It is common practice in emotion research to choose two extreme opposite emotions to study. Hou et al., for instance, found that pleasure and disgust had the highest accuracy when studying emotion classification (Hou et al., 2020). Therefore, in the current study, two opposite emotions were chosen (happy and sad), and a third state (neutral) was used for comparison. First, the power spectral density (PSD) was used to analyze EEG signals. Additionally, a nonlinear dynamics analysis (sample entropy) was performed since the power spectrum analysis cannot be used to assess the nonlinear characteristics of EEG. To explore the relationship between EEG and EMG, we first used transfer entropy to measure the strength of CMC and then used mutual information to build a functional brain network and the knowledge of graph theory to quantitatively analyze its characteristics. Finally, the research results were discussed and summarized. The data processing method used in this study is shown in Fig. 1.

2. Material and methods

2.1. Subjects

The subjects of this experiment were 24 healthy people (14 men and 10 women, all right-handed) aged 23–27 years, who were all graduate students. None of the patients had a history of neurological or psychiatric disease. All participants volunteered to participate in the experiment. Before the experiment, each subject was informed of the detailed experimental process and he/she signed an informed consent form. All experiments in this study complied with the ethical code of the Declaration of Helsinki and were approved by the local ethics committee.

2.2. Experimental design

Before the start of the experiment, we collected 180 movie clips meant to evoke neutral, happy and sad emotions, and then recruited ten volunteers (not experiment participants) to rate these clips. The 20 neutral, 20 happy and 20 sad movie clips with the highest scores were selected, these video clips were extracted from the movies shown in Table 1, and each movie clip lasted for 20 s. The experiment was conducted in a quiet laboratory that was free from magnetic field and noise and was divided into three sessions according to emotion (neutral, happy, sad), each of which the subjects completed in turn. For each session, the subjects watched the corresponding video clips. While watching the videos, the subjects performed 15 grip strength trials (five with 5 kg, five with 10 kg, and five with 15 kg) and five no grip strength trials. In the detailed process, the subject sat in front of the computer screen, the screen played the corresponding video clips, and there were instructions on the upper right of the screen to prompt the subject to complete the corresponding action. At the beginning of the experiment, the corresponding video was played on the screen. To stimulate the emotions of the subjects, the subjects received instructions to grip or not to grip after 15 s of watching the video. The entire grip action lasted for 5 s, and then the subject rested for 10 s before proceeding to the next trial. To ensure the synchronization of the gripping and watching of the video, our grip strength equipment was connected to the subject's palm with a corresponding weight through a rope, so that the subject only needed to pull the weight through the grip when receiving the instruction, without having to look away from the computer screen. After completing one of the emotion exercise sessions, the subject rested for 20 min before beginning the next session. The entire process is illustrated in Fig. 2.

Table 1
20 happy, 20 sad and 20 neutral movie clips with the highest scores.

Number	Happy movie clips	Sad movie clips	Neutral movie clips
1	Mr.Bean (2 clips)	Hachi (2 clips)	Masters In Forbidden City (2 clips)
2	Goodbye Mr. Loser (2 clips)	I Am Legend (2 clips)	Chinese Garden (2 clips)
3	21 Jump Street (2 clips)	Echoes Of The Rainbow (2 clips)	china (2 clips)
4	The Gods Must Be Crazy (2 clips)	Titanic (2 clips)	Peking Opera (2 clips)
5	The Naked Gun:From the Files of Police Squad! (2 clips)	The Curious Case of Benjamin Button (2 clips)	KungQu Of Sexcentenary (2 clips)
6	La Grande vadrouille (2 clips)	One Flew Over the Cuckoo's Nest (2 clips)	A Bite Of China (2 clips)
7	King of comedy (2 clips)	The Godfather: Part 3 (2 clips)	HeXi Corridor (2 clips)
8	The God of Cookery (2 clips)	Amour (2 clips)	Legend Of Tang Empire (2 clips)
9	Drunken Master (2 clips)	To Live (2 clips)	A History Of Britain (2 clips)
10	Kikujirô no natsu (2 clips)	Grave of the Fireflies (2 clips)	Shakespeare Uncovered (2 clips)

2.3. Signal processing

EEG data from this experiment were collected using a 64 channel g. moblab mp-2015 EEG wireless acquisition instrument with a sampling frequency of 1000 Hz. EMG data were collected using the Delsys TrignoTM wireless EMG system with a sampling frequency of 2000 Hz. We collected EEG and EMG data for each trial, as shown in Fig. 1. EEG electrodes were placed according to the international 10–20 system. EEG data were collected from 19 channels (FP1, FP2, Fz, F3, F4, F7, F8, Cz, C3, C4, T7, T8, Pz, P3, P4, P7, P8, O1, and O2) and EMG data from four muscles (flexor digitorum superficialis, extensor carpi ulnaris, flexor carpi ulnaris, and extensor digitorum). Before data processing, the signal was filtered with a 50-Hz notch filter to eliminate the interference caused by the electrical power lines. We used the independent component analysis function in EEGLAB to eliminate the artifacts caused by muscle and eye movement (Delorme and Makeig, 2004), which was achieved by the adjusted plugin in EEGLAB (Mognon et al., 2011).

2.4. Analysis methods

2.4.1. Power spectral density

The PSD of the EEG signals was calculated using the Welch method. The data were normalized to determine the relative PSD.

2.4.2. Sample entropy

Sample entropy, which was proposed by Richman et al. in 2000, is an improved algorithm based on approximate entropy (Richman and Moorman, 2000). It is a nonlinear index used to evaluate the self-similarity and complexity of a time series, with larger values indicating more complexity (Tang et al., 2015).

The sample entropy of an EEG signal with N data is expressed as follows:

$$SampleEn(m,r,N) = -\ln\frac{B^{m+1}(r)}{B^{m}(r)} \tag{1}$$

where $B^m(r)$ is the estimated probability of two sequences matching m points, with the embedding dimension m = 2, a similarity tolerance of 0.25 SD (standard deviation of the EEG time series), and an EEG data length of 5000.

2.4.3. Transfer entropy

Transfer entropy, proposed by Schreiber in 2000 based on information entropy (Schreiber, 2000), is used to measure the directed

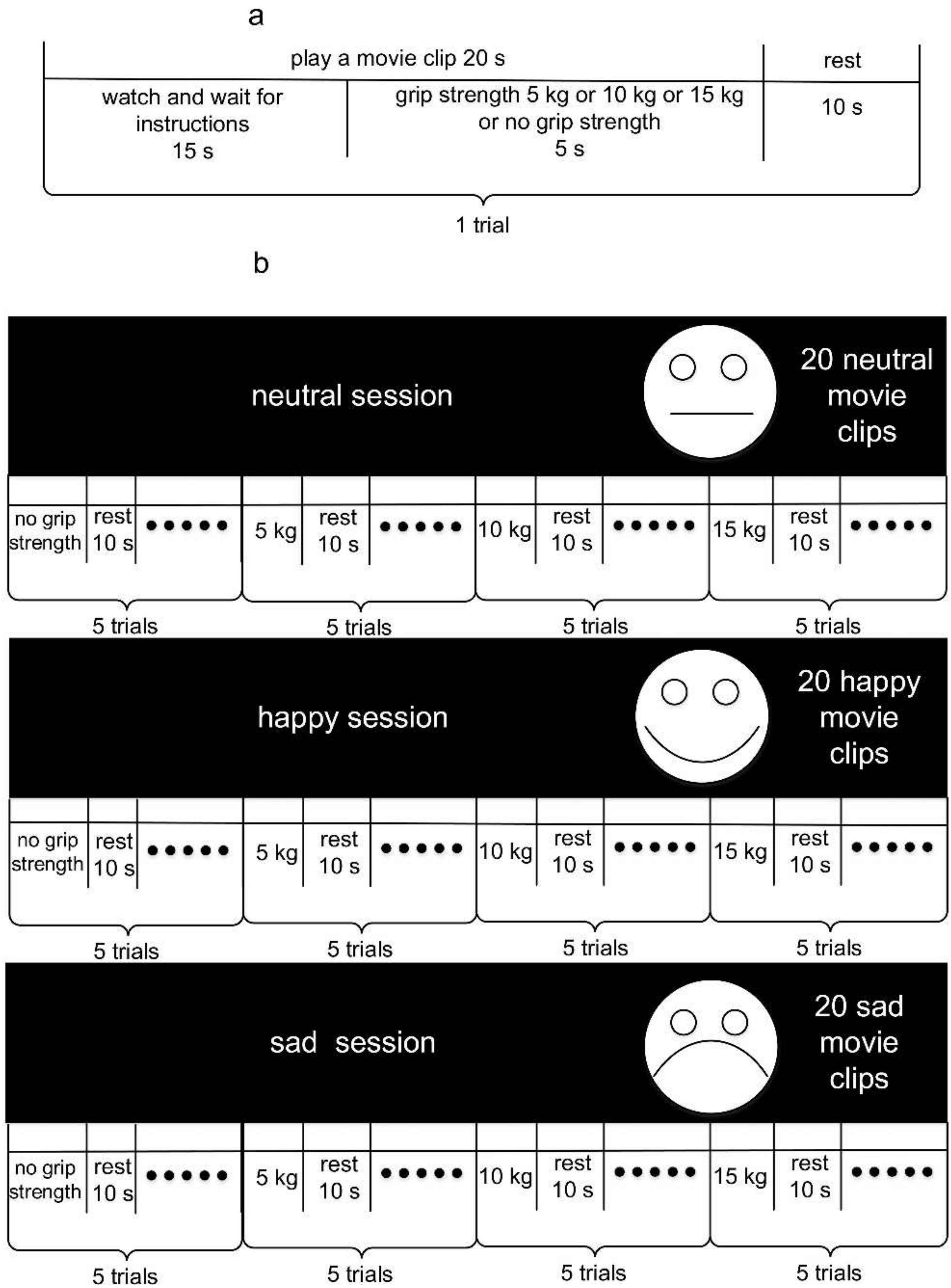

Fig. 2. Design of the experiment: (a) In a trial, the subject watched the video for 15 s according to the instructions, then performed the grip or no grip task for 5 s, and rested for 10 s before the next trial; (b) the experiment was carried out in three sessions, with a rest period of 20 min between each session. There were 20 trials in each session (five with no grip strength, five with 5 kg, five with 10 kg and five with 15 kg).

information transmission between two random processes (Wibral et al., 2014). Therefore, transfer entropy can also be used as a criterion for causality (Murari et al., 2015), usually for biological systems.

For example, given two EEG signal time series X and Y of length T, where $X = \{x_1, x_2, ., x_T\}$ and $Y = \{y_1, y_2, ., y_T\}$, the transfer entropy $TE_{Y\to X}$ represents the amount of information transferred from Y to X. The formula is as follows:

$$TE_{Y\to X} = \sum_{x_{n+\tau}, x_n, y_n} p(x_{n+\tau}, x_n, y_n)\log\left(\frac{p(x_{n+\tau}, x_n, y_n)p(x_n)}{p(x_n, y_n)p(x_{n+\tau}, x_n)}\right) \tag{2}$$

where n is the discrete time index and τ is the prediction time.

2.4.4. Mutual information

Mutual information is an effective measure in information theory, which can be defined as the amount of information contained in one random variable about another random variable (Cover and Thomas, 2005). Assuming that the probability distributions of the S channel and Q channel of the EEG signal are $P_s(s_1), P_s(s_2), ., P_s(s_n)$ and $P_q(q_1), P_q(q_2), ., P_q(q_n)$, the information entropy of S and Q can be expressed as follows:

$$H(S) = -\sum_i p_s(s_i)\log_2 p_s(s_i) \tag{3}$$

$$H(Q) = -\sum_j p_q(q_j)\log_2 p_q(q_j) \tag{4}$$

The joint information entropy is as follows:

$$H(S, Q) = -\sum_{i,j} p_{sq}(s_i, q_j)\log_2 p_{sq}(s_i, q_j) \tag{5}$$

The mutual information of S and Q is as follows:

$$MI(S, Q) = H(S) + H(Q) - H(S, Q) \tag{6}$$

2.4.5. Node degree

The node degree is one of the simplest and most important attributes of a network. It represents the number of edges passing through a node. The greater the node degree, the greater the role of the node in information transmission within the network. The degree of node i is defined as

$$D_i = \sum_{j=1}^{N} a_{ij} \tag{7}$$

2.4.6. Network efficiency

Global efficiency is used to measure the integration capability of a network, specifically, the efficiency of network information transmission. It is the inverse of the average value of the shortest path, which is defined as follows:

$$E_{global} = \frac{1}{n(n-1)}\sum_{i\neq j\in N}\frac{1}{l_{ij}} \tag{8}$$

2.4.7. Statistical analysis

In this study, paired samples t-tests were used to evaluate significant differences in the data, with smaller p-values indicating a greater difference. Further, 95% confidence intervals were selected, and the statistical significance level was set at $p < 0.05$.

3. Results

3.1. Power spectrum density analysis

In this section, we calculated the average PSD of the EEG data of all subjects. Fig. 3 shows the EEG power distribution map with 0.5–30 frequency for the 19 channels. From the results, it can be seen that in the absence of grip strength, compared with the neutral session, the EEG power increased most in the left frontal lobe during the happy session; conversely, the EEG power increased the most in the right frontal lobe

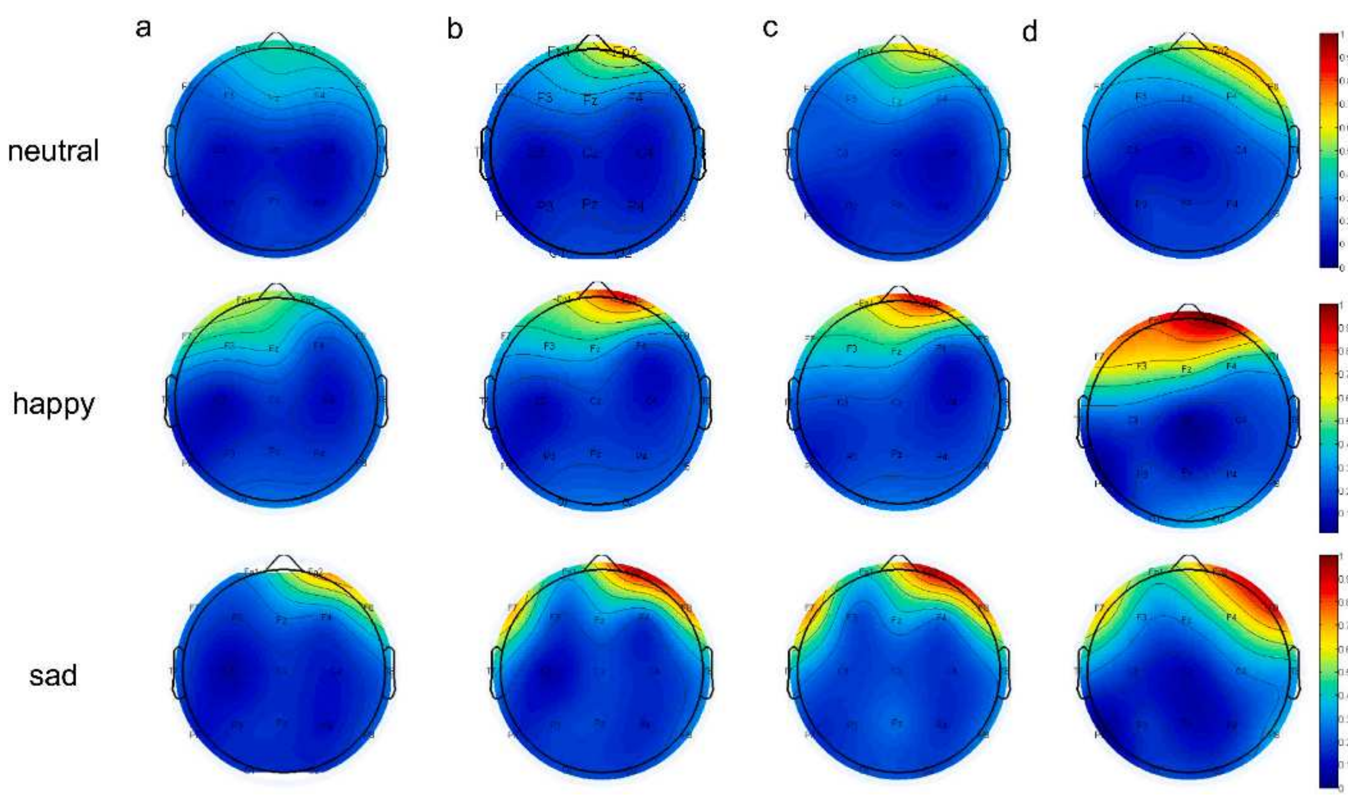

Fig. 3. Average PSD distribution according to emotion and grip strength; (a) no grip strength (b) 5 kg (c) 10 kg (d) 15 kg. The color scale represents the value of the relative PSD. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

during the sad session. When grip strength was added, the EEG power of all grip strengths increased in the right prefrontal lobe during the neutral session, and the same result was observed during the happy session; however, during the sad session, the EEG power of the F7 channel of the left frontal lobe increased significantly. According to the results for the three grip strengths, the EEG power increased with an increase in grip strength during all the sessions.

3.2. Sample entropy analysis

Fig. 4 shows the average EEG sample entropy topographic map for the 19 channels. As can be seen from the Figure, similar to the power spectrum density distribution, with the participation of only emotion, the sample entropy increased most in the left frontal lobe during the neutral session; conversely, the sample entropy increased the most in the right frontal lobe during the sad session. However, after adding grip strength, the sample entropy of the P4 channel increased significantly during all the sessions, and the sample entropy of the C3 channel increased during the happy session, while the sample entropy of the CZ channel increased during the sad session. In general, the grip strength under happy emotions caused a larger increase in the sample entropy of the left hemisphere, and the grip strength under sad emotion caused a larger increase in the sample entropy of the right hemisphere. Lastly, the increase in grip strength from 5 kg to 10–15 kg also led to an increase in sample entropy.

3.3. CMC analysis

Transfer entropy was used to measure CMC strength in this study. Fig. 5 shows the average transfer entropy values of all the subjects at different sessions. According to the results shown in graphs a, b, and c, compared with the neutral session, the transfer entropy in the happy and sad sessions for EEG→EMG was significantly higher (especially happy). According to the results shown in graphs d, e, and f, the transfer entropy in the happy and sad sessions for EMG→EEG was also higher than that in the neutral session. In addition, in the comparison of grip strength, except for no significant difference between 10 kg and 15 kg of the happy session in EMG→EEG, the grip strengths were significantly different.

3.4. Functional brain network analysis

In this study, we used mutual information to construct a functional brain network and analyze the influence of the emotion-movement relationship based on network metrics. The process was divided into three steps. First, the mutual information between the 19 EEG channels was calculated pairwise, thereby obtaining a 19×19 adjacency matrix. Next, an appropriate threshold was selected and the elements greater than the threshold were replaced with “1,” indicating that there was a connection between the two nodes, and the elements less than the threshold were replaced with “0,” indicating that there was no connection between the two nodes. To binarize the adjacency matrix, it was very important to choose an appropriate threshold. We chose the cost efficiency (Ce) threshold (th) as

$$th = \max\{Ce\} = \max\{E_g - D\} \tag{9}$$

where D is the network density, which is defined as the ratio of the actual number of edges to the number of all possible edges, and E_g is the global efficiency. Thus, a binary matrix was obtained. Finally, the graph theory method was used to calculate the network metrics. Fig. 6 shows the average functional brain networks. As can be seen from the Figure, in the absence of grip strength, the network density of the frontal lobe in the happy session was higher than that in the neutral session; while compared with the neutral session, the network connections between the frontal, central and parietal lobes increased in the sad session. After the application of grip, some long-distance network connections

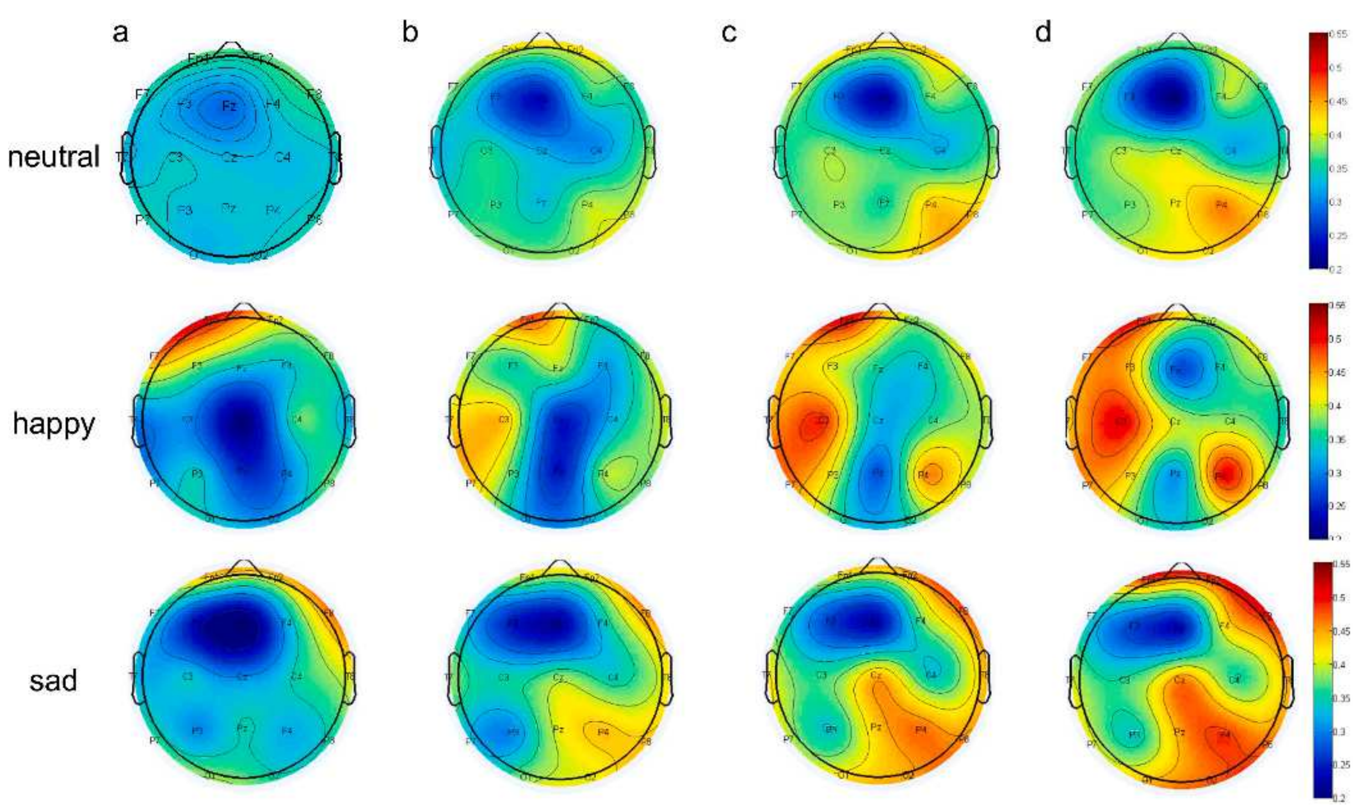

Fig. 4. Average sample entropy distribution according to emotion and grip strength; (a) no grip strength (b) 5 kg (c) 10 kg (b) 15 kg. The color scale represents the value of the sample entropy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

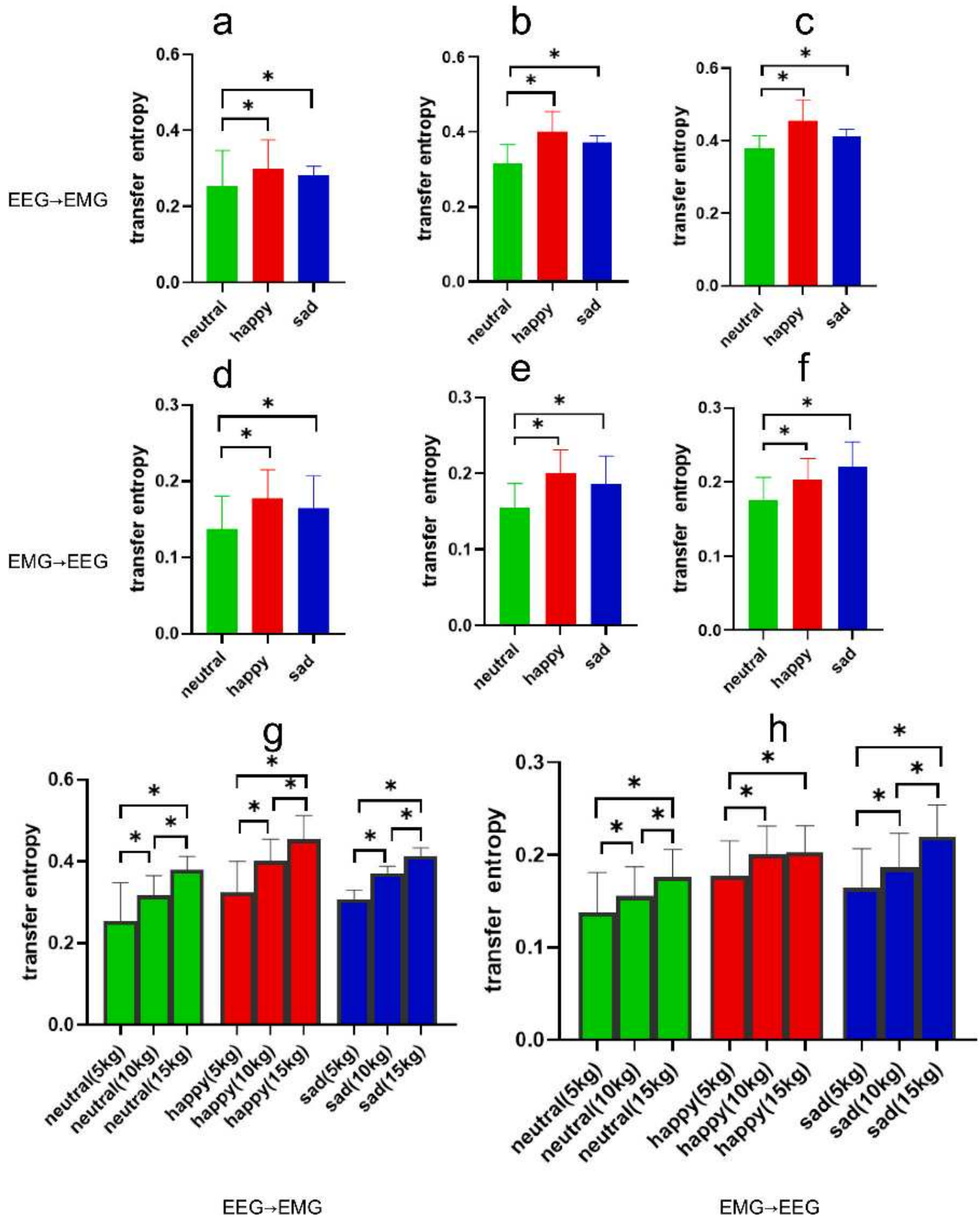

Fig. 5. Transfer entropy according to emotion and grip strength in EEG→EMG and EMG→EEG; (a, d) 5 kg, (b, e) 10 kg, (c, f) 15 kg, (g, h) comparison between 5 kg, 10 kg and 15 kg.

occurred in the brain network, such as the connection from the frontal lobe to the occipital lobe. In addition, increasing grip strength made the brain network more tightly connected.

Fig. 7 shows the node degree of the brain network. It can be seen from graph a that when there is no grip, the frontal region had the largest node degree in the happy session, while the frontal, central and parietal regions had a larger node degree in the sad session. This is consistent with the analysis results of the network connectivity. In addition, it can be seen from the three graphs (b, c, and d) that the occipital region had the largest node degree in the sad session, but with the increase in strength, this characteristic gradually decreased.

Fig. 8 shows the global efficiency of the brain network. The results indicate that network global efficiency in the happy and sad sessions was higher than that in the neutral session. When grip strength was added, the global efficiency of the happy and sad sessions increased, but with the increase in grip strength, the global efficiency did not increase significantly, while the global efficiency of the normal session increased significantly.

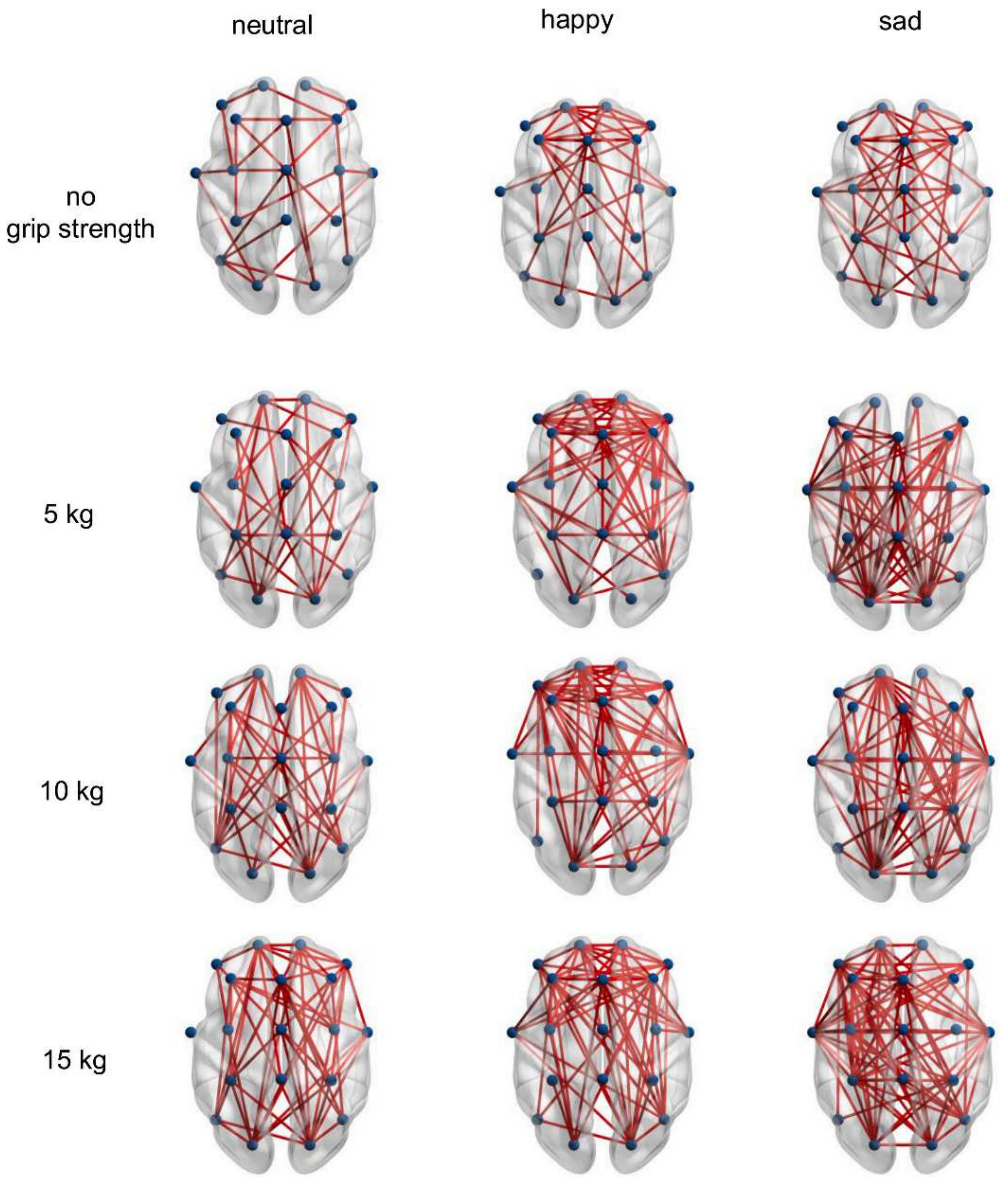

Fig. 6. Average functional brain network according to emotion and grip strength.

4. Discussion and conclusions

In this study, we mainly studied how the emotion-movement relationship affected the cerebral cortex and CMC. For this, we used PSD, sample entropy, transfer entropy, and mutual information to build a functional brain network for analysis.

PSD is commonly used for EEG frequency domain analyses to obtain the energy distribution of EEG signals with frequency variations. In this study, the average power distribution for 19 channels was displayed on a brain topographic map, which clearly showed changes in brain functional activities. We found that grip strength associated with both happy and sad emotions had a high impact on EEG power. The findings that

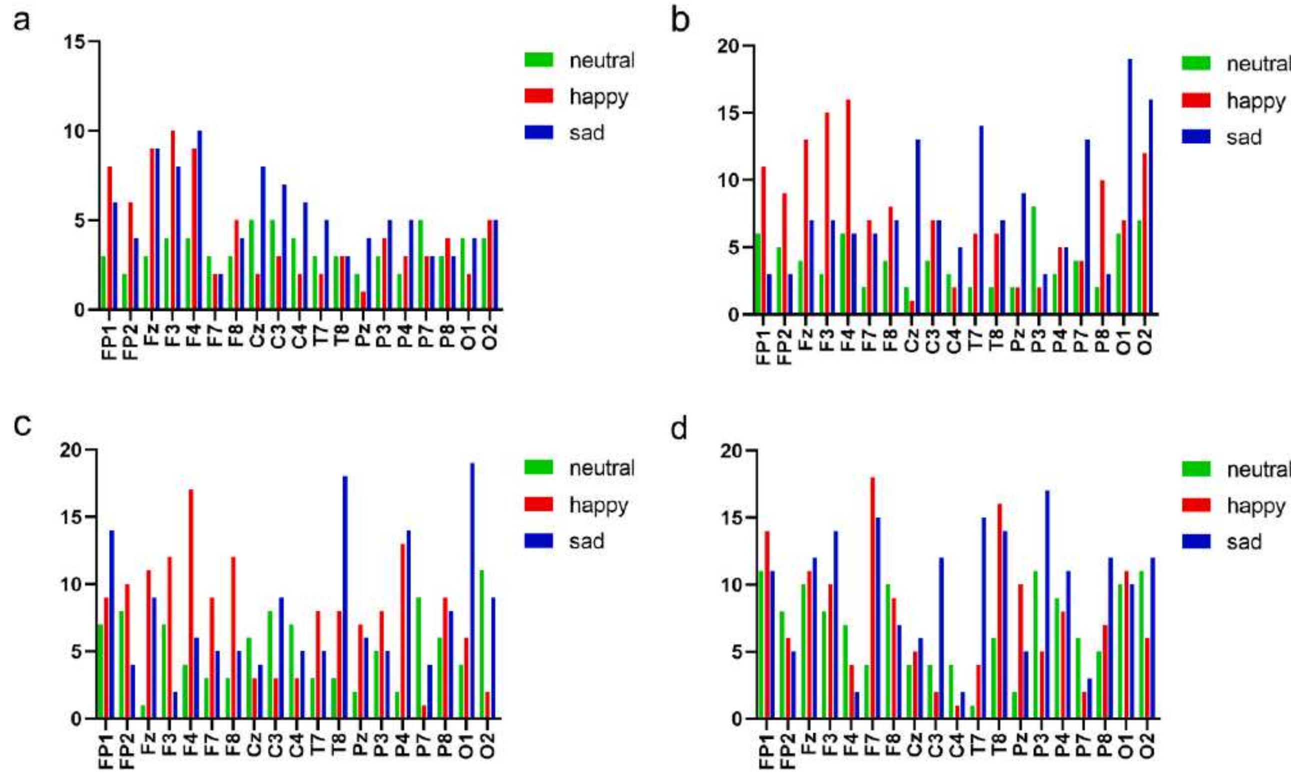

Fig. 7. Node degree distribution for each node according to emotion and grip strength; (a) no grip strength (b) 5 kg (c) 10 kg (d) 15 kg.

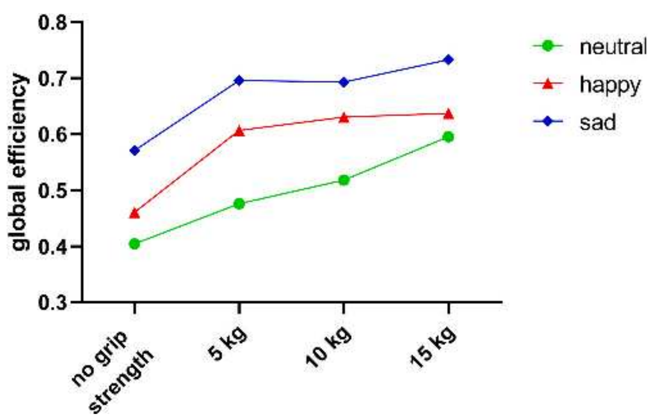

Fig. 8. Global efficiency of networks according to emotion and grip strength.

happy emotions can increase the EEG power of the left frontal lobe and sad emotions can increase the EEG power of the right frontal lobe are consistent with the results of previous studies (Balconi and Mazza, 2010; Waldstein et al., 2000; Wheeler et al., 1993; Davidson and Henriques, 2000). However, we also came to some other conclusions: with the inclusion of grip strength, the frontal lobe EEG power of different emotions showed activation in specific areas, and the grip strength under neutral and happy emotions activated the EEG power of the right prefrontal lobe. On the other hand, the grip strength under sad emotions activated the EEG power of the left frontal lobe, similar to the f7 channel. In addition, grip strength was found to affect the EEG power. For the same emotion, the greater was the grip strength, the higher was the EEG power.

The PSD study mainly focused on changes in the energy of EEG signals in different brain regions, which is a frequency domain analysis method. However, EEG signals are time-varying and non-stationary; therefore, a frequency-domain analysis alone is not sufficient. Sample entropy is a nonlinear analysis method that can be used to quantitatively describe changes in the EEG complex dynamic system and analyze EEG signals more comprehensively. At present, sample entropy has been widely used with EEG, EMG, and other biomedical signals to measure complexity. Sample entropy has been applied previously to sleep staging (Chouvarda et al., 2011), epilepsy detection (Shen et al., 2013), and Alzheimer's disease diagnosis (Abásolo et al., 2006). In this study, the EEG sample entropy distribution of 19 channels was represented using a brain topographic map. Similar to many existing studies, different emotions caused changes in the sample entropy of the frontal lobe (Jie et al., 2014). Happy emotions mainly affected the left frontal lobe, while sad emotions mainly affected the right frontal lobe. In addition, we found that emotion and movement can combine to affect the complexity of the brain, and grip strength in happy emotions increased the complexity of the C3 channel. However, in sad emotion, it increased the complexity of the CZ channel, which led to an obvious difference in brain complexity between the two extreme emotions. Lastly, as the movement pattern (grip strength) increased, the complexity of the brain also increased.

When the human body is moving, the cerebral cortex transmits information to the muscle nerves, and the muscle supplies feedback to the cerebral cortex, demonstrating a two-way coupling process. In this study, transfer entropy was used to measure the strength of CMC. The results showed that the CMC strength of EEG→EMG and EMG→EEG in the happy and sad sessions was higher than that in the neutral session, and that the CMC strength of EEG→EMG was higher than that of EMG→EEG. This shows that happiness and sadness can promote the two-way transmission of information between the cerebral cortex and muscle nerves, and that the primary transmission of information occurs from the cortex to the muscle nerves. This may explain why people experiencing extreme emotions (extreme happiness or sadness) are more able to stimulate the body's potential to do things that are otherwise difficult to accomplish. The results also showed that the CMC strength of EEG→EMG increased with the increase in force for all emotions, but that the CMC strength of EMG→EEG only increased for the neutral and sad sessions.

Functional brain networks can be used to study the collective dynamics of the brain. In this study, mutual information was used to calculate the correlation between each EEG signal. The grip strength associated with different emotions was found to affect nonlinear synchronization between the different brain regions. The results showed that the network connectivity of the brain was different under different emotions. The network connectivity of the frontal lobe increased under happy emotions, while the network connectivity between the frontal lobe, central lobe, and parietal lobe increased under sad emotions. This showed that different emotions could promote the exchange of information in specific brain regions. In addition, grip strength could produce some long-distance exchange of information in the brain regions, and the greater was the grip strength, the tighter was the connection of the brain network.

The greater was the node degree, the greater was the role of the node in information transmission in the network. The results showed that the node degree of the frontal lobe was higher in the happy session, while the node degree of the frontal lobe, central lobe, and parietal lobe was higher in the sad session. This showed that different emotions have important effects on brain network nodes. From the results of network connectivity, we know that grip strength caused a long-distance connection between the occipital lobe and other brain regions, but we found that the node degree of the occipital lobe in sad emotions was higher than that in other emotions from the node degree results, and the difference gradually decreased with the increase in grip strength. This may indicate that the grip strength in sad emotion was more capable of producing this long-distance network connection to the occipital lobe, and this phenomenon became less obvious as the grip strength increased.

This study also analyzed the global efficiency of the brain network, which is often used to measure the network's ability to exchange information. The results showed that the capacity to exchange information during the happy and sad sessions was higher than that during the neutral session. Additionally, with increasing grip strength, the capability of transmitting information during the neutral session increased significantly, while changes during the happy and sad sessions were not as evident.

In summary, this study is the first to combine emotions with human movement. We have selected the following findings as potentially helpful for understanding the mechanism of the emotion-movement relationship: happy emotions increased the power of the left frontal lobe, while sad emotions increased the power of the right frontal lobe. When movement is involved, the power of the right prefrontal lobe in happy emotions increased significantly, and the power of the left frontal lobe in sad emotions also increased. Movement associated with happy emotions can increase the complexity of the left hemisphere, while movement associated with sad emotions can increase the complexity of the right hemisphere. Movements associated with both happy and sad emotions increase the strength of two-way coupling between the cortex and muscles. Functional brain network analysis further demonstrated changes in the network metrics associated with different emotional states. The above findings were compared with those of the neutral session. Different movement patterns also led to different results.

CRediT authorship contribution statement

Xugang Xi: Conceptualization, Methodology, Writing. **Qun Tao:** Software, Writing – original draft. **Jingqi Li:** Supervision, Experiment. **Wanzeng Kong:** Methodology, Supervision. **Yun-Bo Zhao:** Investigation, Conceptualization. **Huijiao Wang:** Validation, Software. **Junhong Wang:** Software.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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