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Effects of Exercise Training on EEG Activity Patterns during Cognitive Tasks

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Abstract: To explore the effective method to detect the effect of exercise training on EEG activity, this paper compared the distinguishability of EEG changes relevanted to exercise training in different cognitive states. EEG signals of college students who have undergone long-term exercise training (exercise training group) and college students who have not undergone such training (control group) were collected under specific cognitive tasks (Motor imagination tasks). Then the power characteristics of alpha wave and beta wave were obtained by wavelet transform method. The machine learning method was used to distinguish the difference of brain electrical activity between the exercise-trained subjects and the control group during the exercise-related cognitive tasks. Results showed that EEG patterns between two groups were not distinguished in rest status (the accuracy is lower than 59%), but they were separable in the completion of the motor cognitive tasks. The accuracy was over 85%. The pattern of brain electrical activity during cognitive tasks can better reflect the effect of exercise training.

Keywords: Exercise training, Machine learning, Brain development.

Introduction

Cognitive neuroscience research shows that learning and training have an important impact on brain development, which is the embodiment of brain plasticity. Exercise ability is not only related to the physiology of organs such as muscles, bones, heart and lung but also related to the brain's exercise information processing ability. The ability of the central nervous system to acquire, recognize and make decisions about movement information is an important part of movement ability. It can be improved too through exercise. The acquisition of motor skills will be accompanied by a certain degree of plasticity changes in brain structure and function with the development of modern imaging technologies such as EEG (electroencephalogram), fMRI(functional magnetic resonance imagion) and PET (positron emission tomography)etc., many researchers have paid attention to the influence of exercise on brain structure and function. On thisbasis, further research was conducted to explore the effects of professional sports training on EEG activity under specific cognitive tasks. These researches can provide physiology basis for evaluation of the training effect and development of motor ability.

Motor ability is one of the basic functions of human brain, and specific training can improve motor abilitiy and affect the physiological structure of the brain. Brain image stdies such as such as fMRI and PET showed that there are specific divisions of brain regions involved in different movements and there are the

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cooperation and interaction of among various motor areas. People with professional sports training showed significant changes in the frontal, occipital and parietal lobes of brain compared with people without sports training group. For example, Wei Gaoxia et al conducted an fMRI study on divers in 2009, and found that the gray matter density in the bilateral thalamus and the left premotor area of elite athletes was significantly higher than that of ordinary people. EEG studies have also shown trainin-related changes in brain electrical activity corresponding to motor function regions. Del Percio et al., (2009) found that the activity of brain regions of air gun athletes in the preparation stage was lower than that of non-athletes. It was found that elite karate athletes had significantly higher amplitudes of rhythm alpha 1 in the top and occipital regions at rest state than non-athletes and amateur athletes. However, these studies were limited in 1) static regional comparisons and didn't compare brain activity patterns during cognitive tasks; 2) The comparison of a single region or parameter fails to analyze the cooperative working mode of multiple regions. The effect of exercise training on brain activity patterns during cognitive tasks remains to be further studied.

In this paper, we will discuss the EEG pattern difference under sport imagine tasks. We compared the EEG activities between the groups of long-term professional sports training and without sports training under exercise-related cognitive tasks. The college students with kong-term professional sports training constituted the experimental group and college students without professional sports training constituted the control group. The EEG electrical signals of the participants were collected during the rest status and the process of performing the motor imagination tasks. Classifiers in machine learning method were used to distinguish the difference of brain electrical activities between the two groups.

Experimental Design

Selection of Experimental Subjects

The subjects of this study were 8 university students in Nanjing with an average age of 23. After the detailed explanation of the experiment purpose and process, the consent form was signed with the subjects on a voluntary basis. In the study, the subjects were divided into professional sports training group and non-professional sports training group according to whether they had received professional sports training. The professional sports training group consists of 4 college students who have received more than three years of professional sports training and carry out more than 5 hours professional training every day. The non-professional sports training group consisted of 4 college students who did not have any amateur or professional sports training. All subjects were in good health and had no mental disorders and no known brain or systemic organic diseases.

Design of Motor Imagery Cognitive Tasks

The cognitive task of motor imagery includes two items. 1) Imaging oneself doing the mental task of sports of high jump. 2) Imagining oneself doing mental task of the swimming action.

Data Acquisition Method

The EEG signal was collected during the mental imagination tasks. The EEG acquisition system produced by Nanjing VISH Company was used to collect EEG signals. The experimental data were collected via 19-lead electrode cap. The brain electrode was placed using international standard 10/20 system in the order of Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Cz, Fz and Pz, referring to the left and right ear electrodes interconnected by electrodes (A1+A2). The arrangement is shown in Figure 1. The EEG data is bandpass filtered from 0.5Hz to 40Hz, and the sampling frequency is 512HZ. In the experiment, it is required to keep the environment quiet and no disturbing noise. The subjects completed the motor imagination tasks in turn under the instruction of the experimental operator:

1) Resting status: Subjects are required to close their eyes and relax without doing any imagination for two minutes.
2) Motor imagination task: The subjects were asked to imagine themselves doing the high jump with their eyes closed and repeat the imagination for one minute. When you're done, stop imagining, open your eyes, relax, and self-regulate for one minute.

3) The subjects were asked to imagine themselves swimming with their eyes closed and repeat the imagination for one minute. When you're done, stop imagining, open your eyes, relax, and self-regulate for one minute.

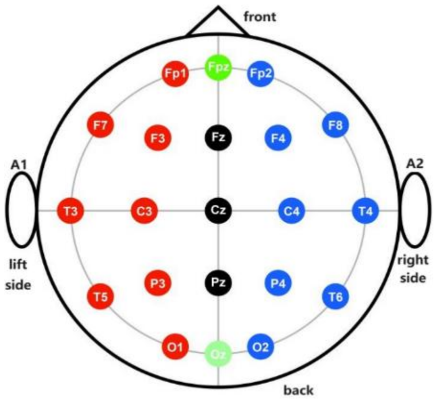

Figure 1. International 10-20 System 19-lead placement

Data Analysis

EEG Feature Parameters Extraction

Data Preprocessing

1) In this experiment, the signal is preprocessed by denoising. Noise was removed for obvious eye movement, body movement or other disturbing manually through the software function.

2) Data segmentation: EEG data of every lead under every task were divided into with a data segment with 512 sample points. 160 data segments were taken per lead for each subject in the resting state. And 160 data segments were obtained for per lead of each subject under the movement imagine tasks.

Feature Extraction

The sampling frequency of EEG experiment data was 512Hz. Considering the frequency range of δ, θ, α and β waves of EEG rhythm, db4 wavelet basis was first used to decompose each original EEG signal in 7 layers. The frequency range of each component after decomposition was corresponding to the frequency band of the four EEG rhythm signals. δ waves mainly appear on A7, θ waves on D7, α and β waves on D6 and D5, respectively. The signal energy coefficents of 4 corresponding bands were calculated. The four signal energy coefficents were normalized to region (Lisberger, 1988). After the pretreatment of EEG experimental data, 4 rhythm energy characteristic parameters were extracted from each data segment after wavelet transformation, and the 19-lead experimental sample was a two-dimensional matrix of 19*4.

Data Pattern Classification Algorithm

In order to determine whether professional sports training has an impact on cognitive brain electrical activity, this study first used the classification algorithm in machine learning to classify the brain electrical activity patterns of the experimental group and the control group to detect whether they are separable. Due to the large number of data features and small amount of data in this study, two classical classification algorithms, SVM (Support Vector Machine) and BP (Back Propagation) neural network algorithms, were employed. SVM is based on statistical learning theory and structural risk minimization principle, which shows many unique advantages in solving small sample, nonlinear and high-dimensional pattern recognition. BP neural network algorithm has strong learning ability, self-organization and adaptability, and can automatically form a decision region that meets the requirements through its own learning mechanism. It has showed the impressive classification performances in the problems without the empirical knowledge and discriminant function about the pattern in advance. So it becomes a classic algorithm in machine learning.

Results and Discussion

Classification Results

In the study, 8 experimental subjects formed 8*160=1280 data samples in rest states and under movement imagine tasks respectively. In each experiment, 70% was used as training data and 30% as test data. The final classification accuracy result was obtained by 10-fold cross-validation.

Experiment 1: Classification of EEG in Rest State

There were 1280 samples with the label of two classes from 4 subjects with long-term professional sport training and 4 subjects non-professional-sport training in rest state. The accuracy was obtained by 10-fold cross-validation. The classification results of experimental group and control group in resting state are shown in Table 1.

Table 1. Classification results of two groups in resting status

Classifier	Accuracy (10-fold)
SVM	58.17%
BP neuronet	53.88%

As it can be seen from the classification results in Table 1, the accuracy of the classification of college students in the professional and non-professional sports training groups was lower than 58.17% under the closed eyes resting task, indicating that the two types of samples were almost inseparable. The results showed that there was almost no difference between the professional training group and the non-professional training group.

This conclusion is similar to that of Coenen (2004). Shishuo et al. where they conducted an exercise imagination experiment on elite male short-distance track cyclists and second-level athletes, and found that there was no significant difference in the total EEG power of the left and right brain regions of second-level athletes compared with elite athletes under quiet state. Denghui studied the EEG of 20 young tennis players (including 4 elite players, 10 elite players and 6 unranked players), and found that the brain wave rate and amplitude of the elite group were not significantly different from those of the elite group and the non-ranked group, which indirectly indicated that the activity degree and tension of the higher nervous activities of the athletes with different training levels were roughly similar when they were quiet. At the same time, Shishuo et al. also believe that the characteristics of EEG at rest are not related to the level of training.

However Zhaoqi and Xuegong (2007) studied the amplitude changes of EEG rhythm in elite karate athletes, amateur karate athletes and non-athletes under the closed eye resting state, and found that the amplitude of δ and α1 rhythm in the parietal region, occipital region and occipital region in elite karate athletes was significantly higher than that in non-athletes and amateur karate athletes. The specific EEG rhythm amplitude of subjects with different training level showed obvious difference. These researches show that there are completely different results on the effects of exercise training on the EEG in the resting state. The inconsistent phenomenon can be explained that EEG in the resting status is unreliable or insufficient to identify the changes in the brain activity of exercise training.

Experiment 2: Classification of EEG Under Motor Imagery Tasks

There were 1280 samples with the label of two classes from 4 subjects with long-term professional sport training and 4 subjects non-professional-sport training under motor imagery tasks. The accuracy was obtained by 10-fold cross-validation. The classification results of experimental group and control group under motor imagery tasks are shown in Table 2.

The classification accuracy of college students in the professional sports training group and the non-professional sports training group was more than 85% under the motor imagination task, and the two types of samples were distinguishable. The results showed that there were significant differences between the professional exercise training group and the non-professional exercise training group. After long-term professional exercise training, the electrical activity of the brain of the college students changed to some extent.

Table 2. Classification results of two groups under motor imagery tasks

Classifier	Accuracy (10-fold)
SVM	87.55%
BP	85.88%

After long-term training, a series of changes have taken place in the structure and function of the system in the higher parts of the brain, and Functional Reorganization is realized to achieve the function reshaping, that is, the plasticity of the brain. The results of experiment 2 showed that this change can be detected explicitly in the cognitive tasks. The change of EEG under cognitive tasks is more distinguishable and relevant to effect of exercise training than the EEG in rest status.

Conclusion

The present study showed that EEG in the long-term exercise professional experimental group and those without professional exercise training was not distinguisable in the resting state. However, there was a significant difference in the pattern of EEG activity in the execution of cognitive tasks, which indicates that the EEG activity in the cognitive task can better reflect the change of motor ability. This result may provide a more accurate perspective for the study of brain plasticity. It also provides a physiological way to evaluate the training effect on brain function. Finally, the change in EEG activity pattern was not only manifested in the band but also in the region. The internal mechanism of this pattern change needs further study.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPESS journal belongs to the authors.

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