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Investigating the modulation of brain activity associated with handgrip force and fatigue

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Abstract.
OBJECTIVE: To investigate the effect of force level and fatigue on brain activity during handgrip tasks.
METHODS: Electroencephalography (EEG) signals were recorded from eleven healthy male subjects when they performed 25%, 50% and 75% maximal voluntary contraction (MVC), and were in fatigue state. EEG powers in different handgrip tasks were analyzed in the frequency domain and time domain respectively.
RESULTS: The EEG power at 25%MVC was significantly lower than that at 75%MVC in gamma band ($p < 0.05$) for electrode C3, C4, Cz, Pz and Fz. EEG power at 25%MVC was also significantly lower than that at 75%MVC in beta band ($p < 0.05$) for electrode C3. However, the handgrip force level and fatigue did not affect the EEG powers for the other frequencies and electrodes ($p > 0.05$).
CONCLUSION: The results suggest that handgrip force level may modulate the brain activity in certain frequency bands and cortical regions. EEG power is a useful tool to characterize the motor state.

Keywords: Electroencephalography (EEG), maximal voluntary contractions (MVC), EEG power, brain activity, handgrip force

1. Introduction

Voluntary motor performance is the result of the brain command driving muscle actions. However, how does a motor task modulate the brain activity is still unknown. Especially, investigations are necessary to understand the influence of force level and fatigue during handgrip task on the brain activity because gripping is one of the fundamental functions of hands.

Recent findings have shown that physical fatigue may result in a reduction in muscle force output and electromyography (EMG) signals. Early research concluded that the primary sites of fatigue lie within muscles [1]. However, recent studies was focused on the fatigue of central nervous system and pointed out that it may result in inadequacy activation to performing muscles [2]. If brain activity related with force level and fatigue can be detected, there will be a way to control motor effectively and facilitate early mobilization and rehabilitation after injury.

Electroencephalography (EEG), as the traditional measurement of brain activity is often considered in the motor control. Many analyses was already applied to the EEG signals, in time and frequency

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domain, during motor tasks of varying muscle force or fatigue levels, such as movement related cortical potential (MRCP) and power spectra or coherence analysis [2–4]. MRCP is usually derived by trigger-averaging numbers of EEG epochs [5]. A previous study calculated fractal dimensions (FDs) from electroencephalography and found a linear relationship with hand-grip force, this supported that FD measure relates proportionally to the brain activity motivating muscle [6]. Independent component analysis (ICA) was used to reveal spatial and spectro-temporal electrocortical properties for different motor tasks [7]. However, FDs and ICA are not easily calculated in real-time system. Another study investigated time-dependent associations between source strength estimated from high-density scalp EEG and force of voluntary handgrip contraction at different intensity levels. It showed there is the lack of significant variations in source strength on different force levels and different cortical areas [8]. Therefore, the influence of handgrip force level on brain activity has not been clearly explained. In order to control movement and alleviate fatigue, it is necessary to understand the effect of hand-grip force level and muscle fatigue on the brain.

The purpose of the present study was to quantify EEG power at varying handgrip force levels and fatigue state. EEG signals from primary sensorimotor regions, supplementary motor area, frontal area and central parietal field were analyzed in the time and frequency domain respectively.

2. Methods

2.1. Participants

Eleven healthy men (average age 22 years, range 21–24 years) volunteered in this experiment. All participants were right-handed assessed by the Edinburgh Handedness Inventory [9]. None of the participants had suffered from a neurological or psychiatric disorder. All participants gave informed consent in accordance with the Helsinki convention for the investigation with human participants.

2.2. Experimental setup

During the experiment, participants sat on a chair with the elbow joint at 100° in front of two computers. Initial maximal voluntary contraction (MVC) was measured in each participant at the beginning of the experiment. The exerted force was displayed on the laptop screen. Then participants were instructed to perform 4 different handgrip tasks according to the cue on the desktop computer screen. The tasks included 25%MVC, 50%MVC, 75%MVC and fatigue state. Each task was repeated five times (five trials) with ten minutes rest following each trial. When a participant grabbed the grip force transducer with 75%MVC until the exerted force dropped over 10% for more than 3 s, it was regarded as fatigue state. The experiment setting is shown in Fig. 1.

2.3. Data recording

EEG and EMG signals were recorded by NeuroScan SynAmps 2 (NeuroScan, USA). EEG was recorded from four midline electrodes (FCz, Cz, Pz, Oz) and 12 pairs of lateral electrodes (FP1/2, F3/4, F7/8, FC5/6, FC1/2, C3/4, T7/8, CP1/2, CP5/6, P3/4, P7/8, O1/2). A total of 28 electrodes were selected according to the international 10–20 electrode system. Bipolar vertical and horizontal electrooculograms (EOG) generated from blinks and eye movement were recorded by four facial electrodes. One electrode was placed at 1 cm above the right eye, one was 1 cm below the right eye, one was at the

Fig. 1. The desktop computer screen displays the start and end cues of the tasks. The laptop screen displays the handgrip force during the tasks.

left outer canthi and the other was at right outer canthi. Surface EMG was recorded from the brachioradialis [10] of right arm using a pair of adhesive electrodes placed 5 cm apart. The ground electrode was located in the center of the EEG electrode array. EEG and EMG were recorded against a common reference electrode at the apex nasi. The electrode impedance was reduced below 5 kΩ by skin preparation before electrode application [11].

A force transducer (YJ-01, Anhui Zhongke Intelligent high-tech Co., Ltd., Chinese Academy of Sciences) was used to measure force level with range of 0$\sim$50 Kg and error $\leqslant$ 1% full scale. EEG, EMG and handgrip force were synchronized with the same start and end cues on a computer.

2.4. *Data analysis*

EEG and EMG were digitized at 1000 samples/s. EEG of 6 s length during the steady force phase was analyzed offline with NeuroScan Scan4.5 (NeuroScan, USA) and custom-written script with MATLAB (Mathworks, USA). The noise signals were removed from EEG and EMG with a 0.5$\sim$50 Hz and a 1$\sim$500 Hz band-pass filter separately. Blinks and eye movements were effectively corrected using a linear regression algorithm [12]. Current source density (CSD) transformations, which could pass activity from the location of interest and suppress other activities, were applied to reduce the effect of volume conduction on EEG signals. An estimate of the current injected into the skull and scalp from the underlying neuronal tissue at a given surface location was computed by CSD with a spatial filter [13].

2.5. *Frequency domain analysis*

Power spectra were estimated by the method of averaged periodograms. The signal sequence $x(n)$, $n = 0, 1, \ldots, N-1$, was divided into K segments with J samples overlapping, each of the segment had L samples. The existing record data were subdivided as: $x_i\ (n) = x(n + i(L - J))$, $i = 0, 1, \ldots, k - 1, n = 0, 1, \ldots, L-1$. The periodogram of the K segments was described by Eq. (1). In this study, $N =$ 6000, $L = 2000$, $K = 5$, $J = 1000$.

$$s_x = (e^{jw}) = \frac{1}{KL} \sum_{i=0}^{K-1} \left| \sum_{n=0}^{L-1} x_i(n + i(L-J)e^{-jwn}) \right|^2 \tag{1}$$

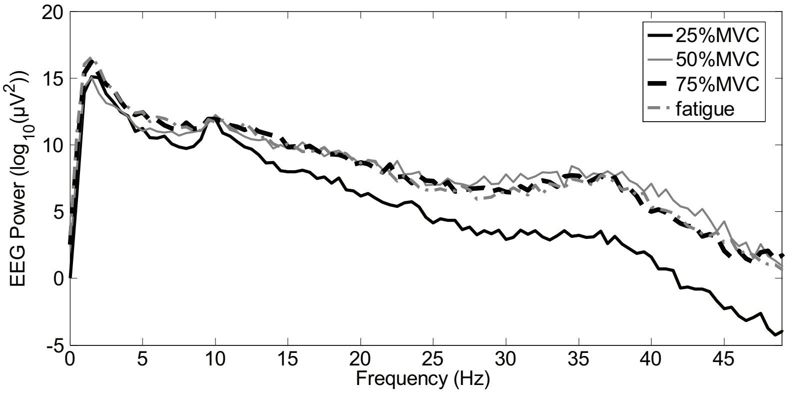

Fig. 2. The EEG power of electrode C3.

Then, the power in the frequency band of delta (1–3 Hz), theta (3.5–7 Hz), alpha (7.5–13 Hz), beta (13.5–30 Hz) and gamma (30.5–45 Hz) was calculated by Eq. (2).

$$E = \sum_{f=f_1}^{f_2} s_x(e^{jw}) \tag{2}$$

where f_1 and f_2 represent the lower and upper frequency in a frequency band.

2.6. *Time domain analysis*

The EEG power by time domain analysis includes the following steps: EEGs of all trials were filtered by 3.5–7 Hz, 7.5–13 Hz, 13.5–30 Hz and 30.5–45 Hz bandpass filter respectively. Then, the amplitude samples were squared to obtain power samples. Next, the power samples across all trials were averaged. Finally, averaging over time samples to smooth the data and reduce the variability [14].

2.7. *Statistical analysis*

Statistical analysis was performed to assess the influence of force level and fatigue on brain activity using software SPSS 14 (SPSS Inc.). The differences of EEG power at 25%MVC, 50%MVC, 75%MVC and fatigue were assessed with one-way ANOVA and Turkey's test.

3. Results

We selected five electrodes overlying major sensorimotor regions. The five electrodes were C3 (contralateral) and C4 (ipsilateral) over the primary sensorimotor regions, Cz over the supplementary motor area, Fz over the central frontal area and Pz over the central parietal field. The mean power spectral density of electrode C3 is plotted in Fig. 2. It illustrated that the EEG power at 50%MVC, 75%MVC and fatigue state had similar trends during the whole frequency band. However, the EEG power at 25%MVC was reduced in alpha, beta and gamma frequency band.

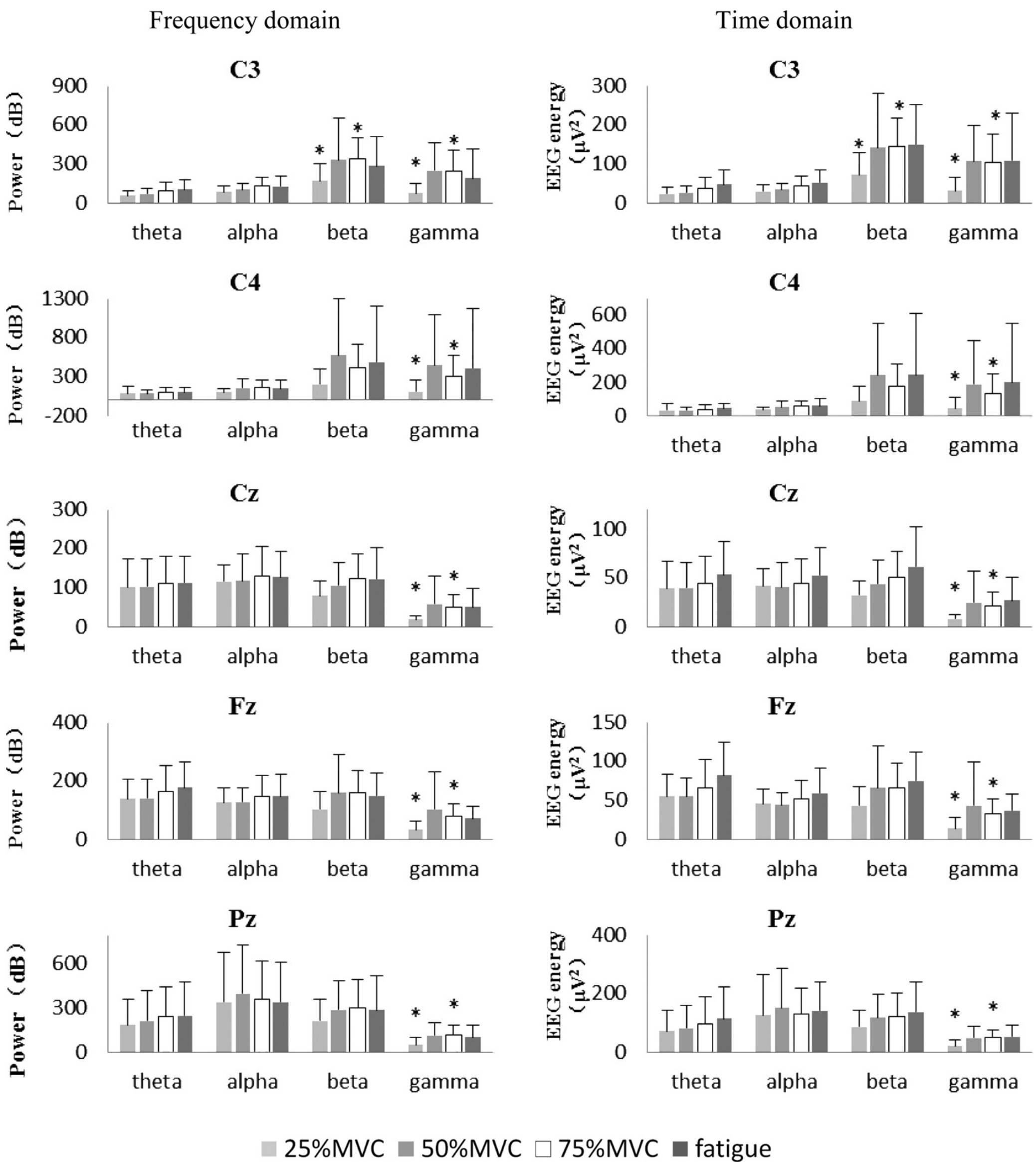

Fig. 3. The EEG power calculated from frequency and time domain. The left column is by frequency analysis and the right column is by time analysis.

The EEG powers within theta, alpha, beta and gamma frequency band at 25%MVC, 50%MVC, 75%MVC and fatigue state were calculated by frequency domain and time domain analysis respectively. The results are shown in Fig. 3.

The results obtained by one-way ANOVA and Turkey's test indicated the EEG power at 25%MVC was significantly lower than that at 75%MVC in gamma band (maximal $p = 0.047$, $p < 0.05$) for the five selected electrodes. Besides, the EEG power at 25%MVC was also significantly lower than that at 75%MVC in beta band ($p = 0.033$, $p < 0.05$) for electrode C3. However, the handgrip force level and fatigue did not affect the EEG powers for the other frequencies and electrodes ($p > 0.05$).

4. Discussion

In this study, we attempted to reveal the influence of handgrip force level and fatigue on brain activity according to EEG power. We found that the EEG powers at 50%MVC, 75%MVC and fatigue state were larger than that at 25%MVC. It may suggest that the brain recruits more motor neurons and increases their firing rates when increasing the force. However, the force more than 50%MVC did not affect EEG power differently. Because fatigue state was defined as handgrip force dropping from 75%MVC to 10% below 75%MVC, which maybe not much difference.

All five cortical locations demonstrated similar pattern of changes in EEG power. This may suggest that the primary sensorimotor cortices (C3, C4) and the secondary cortices (Fz, Pz and Cz) modulate a motor task in a highly coordinated manner, which has also been observed in other EEG and neuroimaging studies [6]. This study may further indicate that different parts of the brain work integrally to achieve a task by synchronous or correlated firing of many neurons at functionally related cortices. The Increment of beta and gamma power is supposed to be an important neural correlation of brain processes for the integration of sensorimotor information. EEG power showed the similar trend as the previous methods such as largest Lyapunov exponent (L1) [15] and fractal dimension (FD) [16], but it was calculated easily.

The results in this study suggest that handgrip force level may modulate the cortical activity in certain frequency bands and cortical regions. EEG power is a useful tool to characterize the motor state.

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