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Brain functional networks analysis of five fingers grasping in virtual reality environment*

Xi Cui, Mengjie Liu, Na Zhang, Jianhong Zhang, Na Wei, Ke Li†, *Member, IEEE*

Abstract— **This study investigated the effects of different center of mass (COM) of the grasping device and visual time-delay on the information interaction between brain regions during five-finger grasping process. Nine healthy right-handed subjects used five fingers to grasp a special device in a virtual reality (VR) environment. Two independent variables were set in the experiment: the COM of the grasping device and the visual delay time. Place a 50 g mass randomly at five different directions of the grasping device base. The three levels of visual delay time appear randomly. The kinematics and dynamics and electroencephalogram (EEG) signals were recorded during the experiment. The brain network was constructed based on multiplex horizontal visibility graph (MHVG). Interlayer mutual information (*MI*) and phase locking value (*PLV*) were calculated to quantify the network, while clustering coefficient (*C*), shortest path length (*L*) and overall network efficiency (*E*) are selected to quantify the network characteristic. Statistical results show that when the mass is located in the radial side, during the load phase of grasping, the *C* and *E* is significantly higher than that in the proximal, ulnar and medial side, and *L* was significantly lower than that in the proximal and radial side. This shows that when grasping an object with a COM bias on the radial side, the process of brain feedforward control has higher level of information interaction and ability and it can build stronger sensorimotor memory. It is also found that the brain network features of theta, beta and gamma bands of EEG are positively correlated, especially between beta and gamma bands, which suggests there is a coupling relationship between different bands in information processing and transmission.**

***Clinical Relevance*— This study explains the neural mechanism of grasping control from the topological structure of the whole brain network level and the informatics.**

I. INTRODUCTION

Grasping is a very important and common action of the hand and the completion of grasping is inseparable from the control of the brain. However, it has been proved that many reasons, such as fatigue and disease, will affect the normal function of hands [1,2]. The neural control mechanism of grasping is still not clearly revealed.

While grasping an object, our brain is provided with a massive amount of information including proprioceptive, visual and tactile inputs that is processed by different neural mechanisms. Precision grasping requires a complex interaction between the feedforward mechanism, which controls digit force to predict external load, and the feedback mechanism, which regulates digit force based on mechanoreceptor signals [3]. When grasping a symmetrically shaped object with asymmetrical center of mass (COM), symmetrical load forces are generated before lifting and quickly adjusted during lifting based on rapid sensory feedback loops [4]. Furthermore, the effects of visual feedback on motion planning and execution have been widely studied [5,6]. Previous studies have shown that visual delay not only altered the force scaling during lifting but also increased the perceived heaviness of lifted objects [7].The brain anticipates the expected event to compensate for the time lag between the visual information available to the brain and the current event when interacting with the environment [8]. In the primate visual system, feedforward influences are carried by theta band (4-7 Hz) and gamma band (31-70 Hz) synchronization, and feedback influences by beta band (14-30 Hz) synchronization [9].

Electroencephalography (EEG) have a relatively higher time resolution, meaning that it has the ability to describe rapid changes in the brain over a short period of time. In recent years, the method of complex network analysis for time series has achieved remarkable development. Multiplex horizontal visibility graph (MHVG) has been shown to inherit the essence of signal correlation dynamics topologically and has been applied to EEG analysis [10].

At present, the research on behavioral neurophysiology in which visual and tactile disturbances coexist is still lacking. So far, it is still unclear how sensorimotor mechanisms rapidly integrate multisensory feedback for online motor control and the neural modulation process has not been clearly explained. The purpose of this study was to investigate the effects of the COM of objects and visual delay on the brain functional networks during grasping. The brain functional network was constructed by multi-channel EEG, and the topology structure of the brain network was analyzed based on graph theory. The mutual information (*MI*) of networks obtained by MHVG [11] and phase locking value (*PLV*) were selected as eigenvalues. It is hypothesized that the external torque deflection and visual delay will cause changes in the brain information interaction and existence of visual time-delay will affect the perception of the deflection torque.

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X.C, M.L, N.Z and J.Z are with the Laboratory of Rehabilitation Engineering, Intelligent Medical Engineering Research Center, School of Control Science and Engineering, Shandong University, Jinan, China.

W.N is with department of Geriatrics, Qilu Hospital, Shandong University, Jinan, China.

K. Li is with the Laboratory of Rehabilitation Engineering, Intelligent Medical Engineering Research Center, School of Control Science and Engineering, Shandong University, Jinan, China (Phone: 15069080366; e-mail: kli@sdu.edu.cn). † K. Li is the corresponding author of this work.

II. Materials and Methods

A. Subjects

Nine right-handed subjects (age: 26.89 ± 3.98 years; height: 166.44 ± 5.13 cm; weight: 62.62 ± 10.64 kg; 4 males and 5 females) participated in the experiment. All subjects were strongly right handed (the Edinburgh handedness inventory scores were 95.56±8.46. All subjects had normal or corrected-to-normal vision, without history of disease or injury of the nervous, muscular, skeletal system or vestibular or cerebellar dysfunction. All the subjects were fully informed the purposes of this study and provided written consent prior to the experiment according to the protocols approved by the Institutional Review Board at Shandong University.

B. Experimental Setup

The experimental device is shown in Fig. 1. Unity3D software are used to provide a VR scene. The VR scene contained the 3D model of grasping device, desk and a suspended platform. The height difference between the platform and the desktop is 15 cm. The grasping device is described in detail in [12]. The five positions where the mass is placed are middle, right, back, front and left sides of the base of the grasping device. The three time-delay are no delay, delay 100 ms and 200 ms respectively.

The EEG signals of 32 channels were recorded under the condition of electrode impedance less than 5 KΩ at a sampling frequency of 500 Hz. The sampling frequency of force/torque sensors is 1000 Hz and the sampling frequency of position sensor is 90 Hz. Use LabVIEW to record EEG, force and position data synchronously.

C. Experimental Procedures

Put the grasping device 30 cm from the edge of the table, aligned with the shoulder of the subject's right hand. Before the formal experiment, each subject underwent a practice experiment to get familiar with the virtual environment and experiment process.

In this task, subjects were asked to lift the device vertically to the same height as the platform in view, and to hold it for 30 s as steady as possible during the hold phase. Nine grasps were performed at each position of the mass, and three times were repeated for each of the three time-delay levels. At the end of each round of nine experiments, the researcher manually changed the position of the mass on the base to change the COM without the subject's knowledge. The time-delay level was automatically changed by a random sequence generated by the program. A total of 45 formal experiments were conducted for each subject. The subjects took 15 s off after each trail of grasping and took a 3 to 5 minutes rest at the end of each round of nine experiments.

D. Data Processing

EEG signals were preprocessed using software BrainVision Analyzer 2.1. EEG signals were band-pass filtered between 4 and 70 Hz and notch filtered at 50 Hz. Independent component analysis (ICA) was used to remove eye movement artifacts in the EEG signals. Forces and position signals were filtered with a fifth order lowpass Butterworth filter with a cut-off frequency of 30 Hz. The theta (4-7 Hz), beta (14-30 Hz) and gamma (31-70 Hz) bands of EEG were extracted by finite impulse response (FIR) filter. Some kinetic parameters and time parameters are calculated: load force (LF) which are the sum of the vertical forces of five fingers, t_{LF0} (the time when LF is greater than 0.1 N), t_{Lw} (the time when LF is equal to the weight of the device) and t_0 (the time when the height of the object is lifted to a height greater than 0.5 mm) are calculated. The period from t_{LF0} to t_{Lw} is considered to be the load phase of the initial grasping movement [13]. The initial movement of an object during lifting is a key visual time point. In this study, different algorithms and eigenvalues were selected to construct the network for the EEG of these two phases: load phase and 1 s after t_0.

In order to build the brain function network, use the following principles, each channel of EEG is converted to a layer of HVG: for a time series X: $\boldsymbol{X}_{\mathbf{t}} = \{\mathbf{x}_i\}_{i=1,\dots,N}$, two time points $\boldsymbol{i}$ and $\mathbf{j}$ are linked if the associated data $\boldsymbol{x}(\boldsymbol{i})$ and $\boldsymbol{x}(\boldsymbol{j})$ have horizontal visibility, i.e. if any value of intermediate data $\boldsymbol{x}(\boldsymbol{k})$ satisfies the ordering relation $\mathbf{x}(\mathbf{k})<\mathbf{inf}\{\mathbf{x}(\mathbf{i}), \mathbf{x}(\mathbf{j})\}$, $\mathbf{k}: \mathbf{i}<\mathbf{k}<\mathbf{j}$. Each channel of EEG can be converted to one HVG, thus the MHVG can be obtained from 32 channels of EEG.

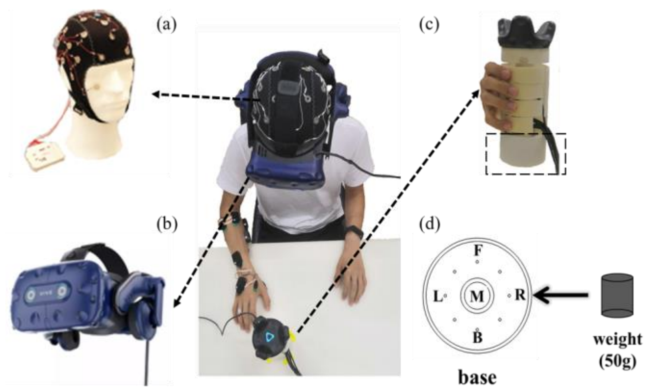

Figure 1. Experiment apparatus: (a) An EEG Acquisition device (Brain Products Inc., LIVEAMP, Germany). (b) The VR helmet: a new consumer-grade head-mounted display (professional-grade VR system, HTC Vive, Tai Wan, China). (c) The grasping device. It is equipped with five six-dimensional force/torque sensors (Nano17, ATI Industrial Automation, Apex, NC, USA) to record the force and moment signals of five fingers in the process of grasping. The position sensor is also installed. (d) The base of the grasping device can be placed with 50 g mass in different directions.

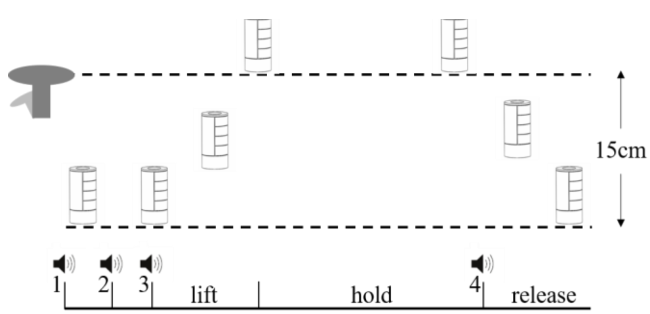

Figure 2. The time line of a trial. The "lift" stage is to touch the device and lift it to the target height after hearing "start", the "hold" stage is to hold it steady, and the "release" stage is to put it back and release it after hearing "over".

We selected the inter layer mutual information as the eigenvalue for the brain network during load phase. $\boldsymbol{MI_{\alpha,\beta}}$ is defined as:

$$MI_{\alpha,\beta} = \sum_{k^{[\alpha]}} \sum_{k^{[\beta]}} P(k^{[\alpha]}, k^{[\beta]}) \log \frac{P(k^{[\alpha]}, k^{[\beta]})}{P(k^{[\alpha]}) P(k^{[\beta]})} \quad (1)$$

where $\boldsymbol{P(k^{|\alpha|}, k^{|\beta|})}$ is the joint probability distribution to count the number of nodes that have degree $\boldsymbol{k^{|\alpha|}}$ in layer α and degree $\boldsymbol{k^{|\beta|}}$ at layer $\boldsymbol{\beta}$.

In addition, we used a sliding window to construct dynamic brain networks of theta, beta and gamma frequency bands during the 1 s period after the object initial movement. The length of this sliding window was 100ms and the step size was 10ms. Select *PLV* to quantitative dynamic brain network characteristic.

For the continuous time signals $x(t)$ and $y(t)$, the phase synchronization relationship can be expressed by the phase locking value.

$$PLV = \sqrt{\left\langle \cos \Phi_{xy}(t) \right\rangle_t^2 + \left\langle \sin \Phi_{xy}(t) \right\rangle_t^2} \quad (2)$$

$$\Phi_{xy}(t) = \Phi_x(t) - \Phi_y(t) \quad (3)$$

Φ_{xy} is the instantaneous phase difference of $x(t)$ and $y(t)$ analytic signals; $\Phi_x(t)$ and $\Phi_y(t)$ are the instantaneous phases of $x(t)$ and $y(t)$ analytic signals respectively.

The nodes of the complex brain networks constructed are electrode points, with the parameters mentioned above as edges. The performance of the above two kind of networks was measured by following parameters in brain functional network based on graph theory, including average weighted clustering coefficient (*C*), average weighted characteristic path length (*L*) and overall network efficiency (*E*). t_i is the number of triangles of node i and k_i is the degree of node i. d_{ij} is the characteristic path length between node i and j while N is the number of nodes.

$$C = \frac{1}{N} \sum_{i=1}^{N} \frac{2t_i}{k_i(k_i - 1)} \quad (4)$$

$$L = \frac{1}{\frac{1}{2} N(N-1)} \sum_{i \geq j} d_{ij} \quad (5)$$

$$E = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \quad (6)$$

The parameters were calculated using MATLAB 2020b (The Mathworks, Natick, MA, USA) with customized code.

E. Statistical Analysis

Statistical analyses were performed using SPSS 25 (SPSS Inc., Chicago, IL). Two-way ANOVA was used to examine the differences of the *C*, *L* and *E* of brain functional networks between different COM position and different levels of visual delay time. Partial correlation analysis is a method for measuring the linear correlation between two variables in multivariate variables under the condition of controlling the influence of other variables and we used it to analyze the correlation of three band of EEG network parameters. A p value of less than 0.05 was considered statistically significant.

III. Results

The brain functional network parameters of different COM objects during load phase of grasping were significantly different. Fig. 3 shows the two-way ANOVA results of the *C*, *L* and *E* of the brain function networks constructed by *MI* under different experimental conditions. When the subjects grasped an object with the COM tilted to the left side, the levels of *C* and *E* in the brain functional network were significantly higher than those in back, middle and right (C: $F = 3.278$, $p < 0.05$; E: $F = 3.283$, $p < 0.05$), and *L* was significantly lower than those in back and right (L: $F = 2.644$, $p < 0.05$). There was no statistical difference in the

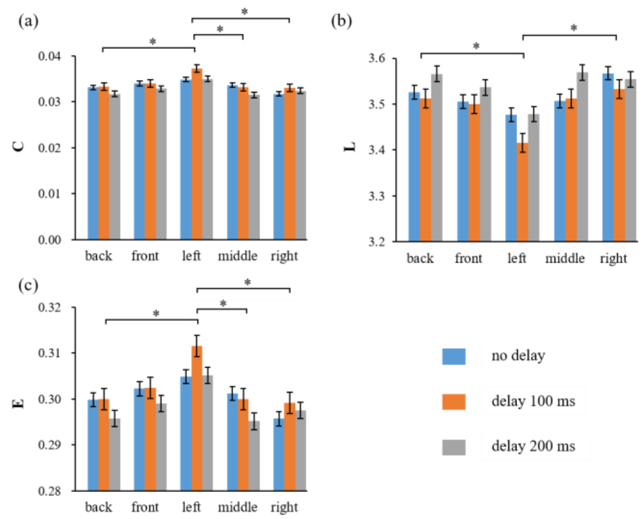

Figure 3. Results of parameters of *MI* brain functional network of full band EEG during the load phase. * Significant difference between the corresponding COM position groups ($p < 0.05$).

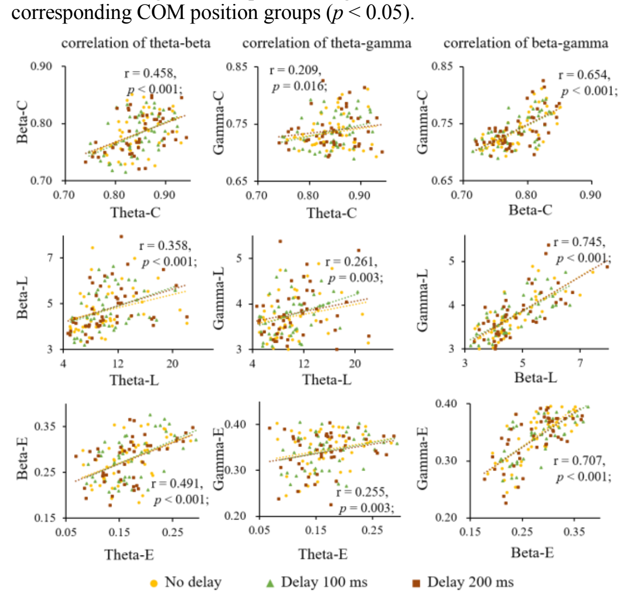

Figure 4. Correlation between pairwise parameters of *PLV* brain networks in the theta, beta and gamma bands during the 1 s period after the object initial movement. (Partial correlation analysis takes time-delay and COM as control factors, and scatter diagram takes three time-delay level as variables to fit three lines.)

characteristics of brain functional networks constructed by *MI* between the three conditions of no visual delay and delay of 100 ms and 200 ms (C: p = 0.565; L: p = 0.437; E: p = 0.546).

We found a correlation between the network parameters of the three bands. Fig. 4 shows the partial correlation analysis results of the C, L, and E networks of the brain function networks constructed by *PLV*. The results show that the parameters of the three bands are positively correlated, and especially the beta and gamma bands are strongly correlated.

IV. Discussion

The purpose of this study was to investigate the effects of external deflection torque and visual delay on brain functional networks during five-finger grasping. We find that when the COM of an asymmetrical object is inclined to the thumb side, during the load phase of lifting, the brain has a higher ability of information interaction. There is a mutual coupling relationship among the brain functional networks of theta, beta and gamma bands.

The load phase is considered to be the period of time between digit early contact and object lift onset. In this period, the load force is applied in an expected manner before feedback about the object's properties is obtained. This expected force regulation is based on sensorimotor memory and is based on online feedback about the fingers position as the position of the finger changes [13,14]. Higher *MI* represents more information interaction. The C and L are two indicators representing functional integration and separation in the functional brain network respectively, while E is often used to characterize the efficacy of the network for information interaction globally. When the COM is to the left, the *MI* network has higher C, shorter L and higher E which indicates that the brain has stronger information processing ability and stronger ability to maintain the balance between functional integration and separation as well as higher information transmission efficiency in the brain. The control of the five-finger follows a two-tier hierarchy, the lower level being the individual fingers (index, middle, ring, little), and the higher level consisting of the thumb and virtual finger (the four fingers combined) [14]. The particularity of the brain network when the COM is tilted to the thumb side, it is speculated that this may be related to the control strategy of the higher level. In a word, the reason for the above difference when the COM is on the left side may be inferred that the brain activity is more active, recruiting more neurons. This may be because the human brain is more sensitive to the thumb side torque perception and has stronger sensorimotor memory. In this study, we did not find the effect of visual delay on the selected network parameters, and speculated that this might be related to the load phase of grasping was not sufficiently time-sensitive or the delay time we set was too short. Future studies will continue to explore the effects of visual time-delay.

The brain functional network constructed by PLV reflects the phase-phase coupling model of the brain. Low frequency oscillations are used to communicate between different brain regions, while high frequency oscillations are spatially local and reflect local cortical processing [15]. The coupling between beta band and other frequency bands is usually seen in exercise experiments or Parkinson's patients. Gamma band is associated with visual awareness, responding to target features such as size and spacing of visual stimuli. The results of network feature correlation analysis among different frequency bands showed a significant positive correlation, which indicated that there was cooperation among the three bands, and there was a coupling relationship between information processing and transmission in the brain functional network. In particular, the strong positive correlation between beta and gamma bands suggested a stronger functional correlation between beta and gamma bands in this task. However, in this study, we only analyzed the pairwise correlation between the network parameters of the three bands, and we will use other methods such as Granger causality to discuss the relationship between multiple variables.

V. Conclusion

In this study, from the perspective of brain functional network, we found the special characteristics of the brain when the right hand grasps an object with the center of mass tilted to the thumb side. Meanwhile, we also found the correlation among the EEG functional networks with different frequency bands. This study provides a unique insight into the neural control mechanisms involved in grasping.

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