Effect of Visual Feedback on Behavioral Control and Functional Activity During Bilateral Hand Movement

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Received: 7 April 2022 / Accepted: 29 April 2023 / Published online: 17 May 2023
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Abstract
Previous researches state vision as a vital source of information for movement control and more precisely for accurate hand movement. Further, fine bimanual motor activity may be associated with various oscillatory activities within distinct brain areas and inter-hemispheric interactions. However, neural coordination among the distinct brain areas responsible to enhance motor accuracy is still not adequate. In the current study, we investigated task-dependent modulation by simultaneously measuring high time resolution electroencephalogram (EEG), electromyogram (EMG) and force along with bi-manual and unimanual motor tasks. The errors were controlled using visual feedback. To complete the unimanual tasks, the participant was asked to grip the strain gauge using the index finger and thumb of the right hand thereby exerting force on the connected visual feedback system. Whereas the bi-manual task involved finger abduction of the left index finger in two contractions along with visual feedback system and at the same time the right hand gripped using definite force on two conditions that whether visual feedback existed or not for the right hand. Primarily, the existence of visual feedback for the right hand significantly decreased brain network global and local efficiency in theta and alpha bands when compared with the elimination of visual feedback using twenty participants. Brain network activity in theta and alpha bands coordinates to facilitate fine hand movement. The findings may provide new neurological insight on virtual reality auxiliary equipment and participants with neurological disorders that cause movement errors requiring accurate motor training.

Graphical Abstract
The current study investigates task-dependent modulation by simultaneously measuring high time resolution electroencephalogram, electromyogram and force along with bi-manual and unimanual motor tasks. The findings show that visual feedback...
for right hand decreases the force root mean square error of right hand. Visual feedback for right hand decreases local and global efficiency of brain network in theta and alpha bands.

Keywords Visual feedback · Theta band · Alpha band · Force accuracy · Network · Efficiency

Abbreviations

| Abbreviation | Description                           |
|--------------|---------------------------------------|
| EEG          | Electroencephalogram                  |
| EMG          | Electromyogram                        |
| MVC          | Maximum voluntary contraction         |
| rFDI         | Right first dorsal interosseous       |
| lFDI         | Left first dorsal interosseous        |
| CSD          | Current source density                |
| Eloc         | Local efficiency                      |
| Eglob        | Global efficiency                     |
| RMSE         | Root mean square error                |
| EMG_CV       | The coefficient of variation of EMG   |
| SD           | Standard deviation                    |

Introduction

Fine motor control requires two types of feedback including intrinsic and extrinsic feedback, extrinsic feedback is primarily visual feedback (Miall 1996; Desmurget and Grafton 2000). It is a fact by a range of studies that visual feedback can improve various motor behaviors, such as force control, upper limb movement and handwriting (Jacobs et al. 1992; Seidler et al. 2001; Sosnoff and Newell 2005). Especially, visual feedback can potentially improve fine hand movement requiring a great deal of accuracy (Elliott and Allard 1985; Lebar et al. 2015). Moreover, visual feedback has been shown to play an important role in visuomotor processing. For instance, in a bimanual precise force gripping task, for the left hand without visual feedback, beta band corticomuscular coherence was only found over the contralateral primary motor cortex instead of contralateral primary motor cortex and supplementary motor area region in the right hand with visual feedback (Chen et al. 2013). Recent studies have shown that visual feedback can increase the complexity of the electroencephalogram during the visuomotor tasks (Shafer et al. 2019). Although many researchers suggested that visual information could make a difference in motor performance and neural processes, however, the topological properties of the brain network connection in this process are still not well understood.
Brain network analysis has been applied in studies of many motor tasks, and the results have indicated that it is a valuable method. Changed topological properties were observed in motor imagination task, motor preparation task and motor execution task (Fallani et al. 2008; Jin et al. 2012; Yu and Yin 2020). Further, empirical evidence has shown the presence of brain network topological properties in visuomotor tasks. Fallani et al. (2010) qualitatively reported the global and local efficiency indexes in healthy participants during visuomotor task using high-density electroencephalogram recording, they showed alpha band tended to increase the efficiency of brain network during the initial period of learning using phase coherence method. Nguyen et al. (2019) reported dynamic network patterns of the different bands through hub structures embody the properties of the brain during the visuomotor task. Although prior researches have confirmed network reorganization with different network characteristics during visuomotor tasks, the effect of visual feedback on network reorganization in terms of separation and integration characteristics of brain functional network during visuomotor tasks has not been investigated. We use the local efficiency and global efficiency to measure the robustness property and the information transfer efficiency of network during visual feedback tasks. We hypothesized that visual feedback can decrease local efficiency and local efficiency during steady-hold hand movement.

There is abundant evidence across many studies showing that functional processing of information input was associated with different band-specific neural oscillations in movement (Bauer et al. 2014; van Pelt et al. 2016; Lebar et al. 2017). Theta band was related to the movement observation, cognitive control processes and strategy adjustment of action in multiple brain areas (Cohen 2011, 2014; Duprez et al. 2020; Yordanova et al. 2020). The alpha band serves as a local marker for the degree of excitability of the somatosensory and visual cortices, with a lower alpha power being related to higher activity level (Lebar et al. 2017). Beta oscillations are obvious during steady states when participants perform visually guided motor control activities (Mehrkanoon et al. 2014). The processing or somatosensory integration is related to beta desynchronization (Lebar et al. 2017). Gamma oscillations contribute to a higher order of sensory information integration to deal with unimodal and multimodal sensory binding and encode stimuli of different sensory modalities (Kreber et al. 2015). These researches suggested that neural oscillations in different bands may process distinct functions. Thus, we analyze network properties in theta, alpha, beta and gamma bands during steady-hold hand movement.

The modulation of visual input might be involved in several brain areas. For instance, visual information would project primary processing in the occipital pool (Livingstone and Hubel 1988). Recognition and identification of the intricate visual process were involved in the temporal region (Newsome and Pare 1988; Tankus and Fried 2012) whereas the spatial representation were related to the posterior parietal region (Cavdaroglu and Knops 2019). The visually-guided motor activity involved multiple brain areas that coordinate to facilitate movement performance. Dipietro et al. (2014) found that the frontoparietal network was related to visually guide upper limb movements. Besides, the corpus callosum connects the cerebral hemispheres on both sides at the anatomical level and it mainly participates in the exchange of information across the two hemispheres for functions including organization of bimanual movement, integrating feeling and vision (Netz et al. 1995). The studies discussed above state that online visual-motor correction of bilateral hand movement involved multiple areas were distributed in different functional cortex. Thus, we analyzed the underlying neurophysiological process from the perspective of the whole brain network based on graph theory during the visuomotor task. Bimanual motions are important for humans in daily life since a lot of tasks require cooperative the bimanual hands to achieve the goal. Thus, studying the network characteristic during bimanual task is significant.

Different types of neural processing were reflected through different carrier frequencies, embodying the impact on frequency-dependent networks during visually-guide sustained contraction. Thus, the purpose of this research was to study the impact of visual feedback on the brain network through different frequencies. We performed bilateral and unilateral hand movements and controlled the movement errors using visual feedback. The unique force was exerted from the right hand with visual feedback in the unimanual task and in the bimanual tasks, conditions were divided into four tasks based on whether visual feedback existed for the right hand and two contraction levels of the left-hand muscles. Based on graph theory analysis, network efficiency was used to capture the efficiency of information transfer and the assembled characteristics underlying the observed functional network.

**Methods**

**Participants**

22 healthy participants with normal or corrected-to-normal vision were involved in the unimanual task and bimanual tasks. This study was in accordance with ethical guidelines laid down in the current version of Helsinki declaration. All participants signed informed consent and the experiment was approved by the Ethics Committee of Medical College of Xi’an Jiaotong University. The healthy participants were students and recruited from Xi’an Jiaotong University. Participants with a history of psychiatric disorders and those
having any physical illness that can affect hand movement were excluded from the study. Participants include 21 right-handed participants and one left-handed participant. In this study, to remove the possible effect of handedness, a left-handed participant was excluded from the subsequent analysis. One participant conducted three bimanual task blocks (It should be seven task blocks) and was excluded from following analysis. The average age of the participants was 21 years and the age ranged between 21 and 24 years.

**Experimental Design and Task**

The baseline task was a right-hand unimanual precision grip using the index finger and the thumb pinching a force sensor (s-type tension–compression sensor, full scale: 1 kg, Bengbu Sensor System Engineering Co., Ltd, China) to exert a 2-N force connected to the visual feedback system. The bimanual tasks were to abduct the index finger of left hand to exert two types of force involving 5% maximum voluntary contraction (MVC) and 50% MVC by pressing another force sensor (s-type tension–compression sensor, full scale: 10 kg, Bengbu Sensor System Engineering Co., Ltd, China). The participant sat in the chair and the 19” monitor was in front of the participant (Fig. 1). The distance between participant and monitor was about 100 cm. The monitor showed visual feedback of the exerted force and target force. In half of the task, the visual feedback will disappear and the participant needs to maintain exerted force in the maintenance phase. Therefore, based on the contraction level of left-hand muscles and whether visual feedback exists or not for the right hand, the tasks had four task conditions, naming ‘RF-L5’, ‘RF-L50’, ‘R-L5’, ‘R-L50’, where ‘RF’ represented with visual feedback of right hand, ‘R’ represented without visual feedback of right hand. ‘L5’ represented left hand need to exert 5% MVC, ‘L50’ represented left hand need to exert 50% MVC. ‘RF-L0’ represented the unimanual task.

The duration of each trial was 6 s. The participants adapted applied force to target force in the first 2 s and during the next 4 s the participants maintained the target force with or without visual feedback during the steady-hold period for the right hand. At the end of each trial, the participants rested for about 1.5 s. During the resting time, visual feedback of both hands was eliminated before the next trial was conducted. The whole experiment included one unimanual task block and seven bi-manual task blocks. The unimanual task block contained 60 trials and every bimanual task block contained 40 trials. Each bimanual task block contained 4 conditions, each condition contained 10 trials, 40 trials were distributed randomly.

Participants adjusted the exerted force through the visual feedback on the screen. The screen contained two pairs of rings that included a solid circle and a hollow circle. The participant should move the solid circle into the hollow circle. The upper part displayed a pair of circles. According to the distance from the hollow circle, it was divided into 50% MVC and 5% MVC for the left-hand muscle. The bottom of the screen displayed a pair of circles showing the performance of the right hand. Figure 2 showed the schematic of the experiment process.

**Data Acquisition and Preprocessing**

The participants were sitting in a dim and electromagnetic shielded room. SynAmps² system (Neuroscan, El Paso, TX, USA) recorded high-resolution EEG and EMG data. EEG signal was acquired from 60 mounted Ag/AgCl channels that were positioned according to the international 10–20 system. The signal was referenced with respect to the vertex. Electrooculography was monitored by four separated channels that were positioned around the eye. Two electrodes were used for EMG that was positioned at the right and left first dorsal interosseous (rFDI and lFDI) muscle. The ground electrode of EEG and EMG was positioned on the midline of the scalp at the level of the prefrontal cortex. EEG and EMG signals were amplified (EMG: bandpass, 5–100 Hz; EEG: bandpass, DC to 100 Hz) and were sampled at 1000 Hz. During the recording session, the impedance of each channel was maintained below 5 kΩ. Two force sensors were used to record the force exerted by the participants simultaneously. The force signal was digitized at 200 Hz.
A block diagram of EEG, EMG and force signal processing and analysis pipeline is shown in Fig. 3. First, a zero-phase finite impulse response filter was applied with a high-pass at 0.1 Hz and low-pass at 45 Hz. Electrodes with artifacts were recounted with topographic interpolated using surrounding channels. Raw EMG signal was high-pass filtered at 5 Hz. The filtered EMG signals were rectified by taking the absolute value. The rectified data was a low-pass filter at 5 Hz. The filtered EMG signals were baseline-corrected using the entire epoch to remove the linear trends. Third, EEG, EMG and force signal of epoch 8 s was extracted which included 1 s before movement and 1 s post-movement. EEG was baseline-corrected using the entire epoch to remove the linear trends. Finally, epochs with the amplitude of steady-hold of the right hand above ±50% target force were rejected. The discarding epochs were 9.8 ± 7.7 for the participants (N = 20). All preprocessing was conducted using EEGLAB (14_1_1b) and MATLAB 2018b (The Math Works Inc.). Then, the surface segmented EEG was transformed into the reference-free current source density (CSD) estimates implementing scalp surface Laplacian using a spherical spline algorithm (Perrin et al. 1989). Scalp surface Laplacian is a fine approximate evaluation to be proportional to the dura potential (Nunez 1987), and can remove nearly all volume conduction errors (Nunez et al. 1997). The spherical spline algorithm was conducted in the CSD toolbox (version 1.1) (Kayser and Tenke 2006a,b).

Data Analysis

The first step for EMG analysis was to calculate the activation level of each muscle in the time domain, we analyzed raw EMG signal in every task to get EMG activity. The process is as follows: (1) The raw EMG signals were off-line high-pass filtered at 10 Hz. (2) The filtered EMG signals were rectified by taking the absolute value. (3) The rectified data was a low-pass filter at 5 Hz. (4) The filtered EMG signals were baseline-corrected using the entire epoch to remove the linear trends. (5) To obtain the mean EMG activity for all participants, the processed data was averaged across all trials and participants in each condition (Chen et al. 2013). In the following, we use the term ‘EMG activity’ for this preprocessed EMG. After processing, CSD, EMG, and force data within steady-hold periods during which the accuracy was obtained around a target were used for further analysis.

Brain Network Formation

In this study, we consider each CSD signal as a representation of the underlying brain function. The spectral coherence is estimated from each pair of electrodes. Each electrode of the CSD signal is considered as a vertex in the formed brain functional network. The connection strength is assigned to each edge by its corresponding spectral coherence value from a weighted graph. To formally
define the above-described procedure, we denote \( m^k_x \) and \( m^k_y \) as the analytic signals of EEG electrodes, \( x \) and \( y \) in the \( k \)th epoch of one condition, the vertical bar surrounding signal \( x \) and \( y \) mean the magnitude of them, \( \phi_{xy}^k \) means the phase angle difference between signal \( x \) and \( y \) in the \( k \)th epoch at specific condition, \( t \) means trials points. The phase was obtained by wavelet analysis using complex Morlet wavelet, the concentrated frequency range from 4 to 45 Hz in a step of 1 Hz, the number of cycles of the Gaussian taper increase from 4 to 8 in logarithmic scaling with the increasing frequency of wavelet from 4 to 45 Hz. Thus, the spectral coherence between two channels at each frequency \( f \) could be found as follows.

\[
C_{xy}^k(f) = \left| n^{-1} \sum_{t=1}^{n} m^k_x(t) m^k_y(t) e^{i \phi_{xy}^t} \right|^2
\]  

(1)
where sum and \( n^{-1} \) indicate the average over magnitude-modulated phase value. The obtained spectral coherence is between 0 and 1. Spectral coherence is 1 if two signals are perfectly coherent, spectral coherence is 0 if they are totally independent. In each condition and frequency band, the average spectral coherence is calculated as:

\[
S_{xy}^k(f) = \frac{C_{xy}^k(f)}{(n^{-1} \sum_{l=1}^{n} |m_{xy}^k|^2)(n^{-1} \sum_{l=1}^{n} |m_{xy}^l|^2)}
\]

where \( l \) is the number of the epoch in each task condition. With the estimated connectivity measure, we have constructed the adjacency matrix \( A \) of the proposed brain network. The adjacency matrix \( A \) is given as:

\[
A = \\
\begin{bmatrix}
A_{1,1} & A_{1,2} & \ldots & A_{1,M} \\
\vdots & \vdots & \ddots & \vdots \\
A_{M,1} & A_{M,2} & \ldots & A_{M,M}
\end{bmatrix}
\]

where \( M \) is the total number of electrodes available and each element in \( A \), denoted as \( A_{xy} \), represents the connection strength between the \( x \)th and \( y \)th channel (Bullmore and Sporns 2009). The value of \( A_{xy} \) is given as:

\[
A_{xy} = \frac{\bar{S}_{xy}(f)}{	ext{condition, frequency}}
\]

where \( \bar{S}_{xy} \) denotes the average spectral coherence value at given frequency band and condition between the \( x \)th and \( y \)th channel.

### Network Analysis

With the obtained task-related brain network, efficiency was employed to study its topographic properties. The graph measure collapsed the overall topological features of a given brain functional network into a single measurement. Therefore, it facilitates the comparison of the obtained brain network between different tasks in normal. The weighted graph version of the two graph metrics, namely, local efficiency (Eloc) and global efficiency (Eglob) were selected due to their novelty in the brain functional network analysis (Wang et al. 2010). To mathematically define these graph measures, we first denote connection weighted \( A_{ij} \) as the link between the \( i \)th node and the \( j \)th node, where \( G \) is the set of all possible vertex of the obtained brain functional network, and \( n \) is the number of nodes, \( d_w = \sum_{u,v \in G} f(A_{uv}) \), where \( f \) is a map (e.g., an inverse) from weight to length and \( g_{u \leftrightarrow v}^w \) is the shortest weighted path between \( u \) and \( v \), \( w \) means weighted graph, \( a_{uv} \) is the state of the connection between \( u \) and \( v \).

The global efficiency is developed to overcome the difficulties inherited in the characteristic path length. It differs from the characteristic path length by using the reciprocal value of the shortest path length. Global efficiency supports the efficient transfer of parallel information at a relatively low cost. Global efficiency is a reliable measure to study functional integration. It is defined as:

\[
E_{\text{glob}}^w = \frac{1}{n} \sum_{i \in G} \frac{1}{n-1} \sum_{j \in G \setminus i} \frac{1}{d_{ij}^w}
\]

The local efficiency represents the fault tolerance of the network. The local efficiency of a weighted graph represents the function separation. It is defined as follow:

\[
\text{Eloc}_{i}^w = \frac{1}{n} \sum_{j \in E^i} \text{Eloc}_j^w = \frac{1}{n} \sum_{i \in E^i} \text{Eglob}_{i}^w(G_i)
\]

where \( G_i \) denotes the subgraph consisting of neighbors of node \( i \) excluding node \( i \) itself. For details on the graph measures, please refer to (Rubinov and Sporns 2010).

So as to capture the graph measures among these networks, the networks need to be properly pruned so that the false connections can be reduced while keeping the threshold to trim the connection with sub-threshold strength. After selecting the sparsity, the graph measures were computed and the sparsity level was selected by using the following procedure. First, the graph sparsity was defined as the fraction of preserved strongest connection to the total number of all possible connections in the obtained network. Then, band-wise matrices were thresholded to retain between 10 and 50% of the largest coherence value. The sparsity of 10% insured that mean degree \( K \geq 2 \times \log(V) \), \( V = 60 \) nodes, this boundary ensured the graphs were estimable (Chennu et al. 2014; Albrecht et al. 2016). Besides, above the sparsity of 50%, the networks tend to be random and less small-world increasingly (Chennu et al. 2014). At each value of the sparsity, the global and local efficiency were calculated across the thresholded and weighted matrices for the individual network in each band and condition using Brain Connectivity Toolbox in MATLAB (Rubinov and Sporns 2010). All network results reported are average of sparsity range 10–50% (41 values, 1% steps) in this study.

### Force Accuracy, EMG Steadiness and EMG Activity

Force accuracy was measured by root mean square error (RMSE) (Wang et al. 2018), which was defined as the following equation:

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}
\]
RMSE \_n = \left( \frac{\sum_{i=1}^{N} (s - f_i)^2}{N} \right)^{\frac{1}{2}} \tag{8}

\( n \) is the \( j \)th data epoch, \( s \) is the target force, \( f_i \) is the \( i \)th force sample, \( N \) is the number of the sampling point.

We determined the coefficient of variation of EMG as measures of EMG steadiness (EMG\_CV). EMG\_CV was defined as following (Graziadio et al. 2010; Long et al. 2016; Ahamed et al. 2017):

\[ EMG\_CV \_n = 1 - \frac{SD(EMG_{n,\text{rectified}})}{mean(EMG_{n,\text{rectified}})} \tag{9} \]

\( n_{\text{rectified}} \) is the \( j \)th rectified EMG epoch. \( SD \) denotes standard deviation of the \( j \)th rectified EMG epoch, \( mean \) shows the average value of the \( j \)th rectified EMG epoch and \( EMG\_CV \_n \) is the value of coefficient of variation of the \( j \)th rectified EMG epoch.

### Statistical Analysis

In this study, we used two steps of statistical analysis to test the hypotheses. First, we used RF-L0, RF-L5 and RF-L50 to test how the left-hand muscle at the different level influence the force RMSE, EMG\_CV, global and local efficiency using repeated measures repeated-measure ANOVA. Second, we used two-factor within-subject repeated measure ANOVA analysis between conditions RF-L5, R-L5, RF-L50 and R-L50 with 20 participants to test the effect of the contraction level (5% and 50% of MVC) of the left hand and visual feedback for the right hand on the RMSE of the exerted force, EMG\_CV, the local efficiency and global efficiency of the network during the steady-hold period. The post hoc test was corrected by the Holm-Bonferroni measure. Significance was set at \( p < 0.05 \). Group data are presented as \( M \pm SD \). Statistical analysis was carried by using Statistical Product and Service Solutions (IBM SPSS Statistics, version 22).

### Results

#### Behavior Performance

Figure 4 shows the average behavior results for all participants performing the ramp-hold precision hand task during RF-L0, RF-L5, R-L5, RF-L50, R-L50. Figure 4a, b show the time course of average forces and average EMG activities of both hands for each condition respectively. Figure 4a represents trajectories range of exerted force across all the participants at every sampling point. The shaded areas represented maximum and minimum range of the mean force of exerted force of each participant across all the participants at every sampling point. Figure 4b shows the mean EMG activity within a specific range, these results represented that participants met the experiment requirements under every task.

#### Force RMSE and EMG\_CV

Force RMSE was average across all participants for the right hand (Fig. 5). To verify whether different conditions had a significant influence on right-hand muscle activities, we used the two-steps statistical analysis. The mean force RMSE was 0.073 ± 0.032 for task RF-L0, 0.097 ± 0.030 for task RF-L5, 0.159 ± 0.067 for task R-L5, 0.116 ± 0.042 for task RF-L50 and 0.152 ± 0.056 for task R-L50. In the first-step statistical analysis, the results of ANOVA showed that the force RMSE differed between conditions RF-L0, RF-L5 and RF-L50 \( (F = 28.412, df = 2, p < 0.001) \). Further post hoc analysis showed significant differences between conditions RF-L0 and RF-L5 \( (p < 0.001) \), RF-L0 and RF-L50 \( (p < 0.001) \), RF-L5 and RF-L50 \( (p = 0.022) \) in force RMSE (Table 1). In the second step of the statistical analysis, a two-factor within-subject repeated-measures ANOVA was used to analyze the influence of visual feedback and the contraction level of left-hand muscles for the right hand on the force RMSE. The ANOVA results showed that the visual feedback significantly influenced the force RMSE \( (F = 34.301, df = 1, p < 0.001) \). The contraction level of left-hand muscles had no significant influence on the force RMSE \( (F = 0.914, df = 1, p = 0.351) \) (Table 2). The interaction of visual feedback x contraction level of left-hand muscle was significant \( (F = 10.472, df = 1, p = 0.004) \). Post hoc test showed that force RMSE increased significantly during condition RF-L50 compared with that during RF-L5 \( (p = 0.007) \), however, the difference was not significant between condition R-L5 and task R-L50 \( (p = 0.402) \). Meanwhile, force RMSE increased during condition R-L5 compared with task RF-L5 \( (p < 0.001) \) and during condition R-L50 compared with task RF-L50 \( (p < 0.001) \).

EMG\_CV were averaged across all 20 participants for rFDI during each condition (Fig. 6). The mean EMG\_CV was 0.107 ± 0.051 for condition RF-L0, 0.127 ± 0.064 for condition RF-L5, 0.123 ± 0.071 for condition R-L5, 0.132 ± 0.062 for condition RF-L50 and 0.132 ± 0.065 for condition R-L50. In the first-step statistical analysis, the results of ANOVA showed that the EMG\_CV differed between conditions RF-L0, RF-L5 and RF-L50 \( (F = 7.020, df = 0.026) \), RF-L5 and RF-L50 \( (p = 0.014) \). Further post hoc analysis showed no significant difference was found between RF-L0 and RF-L5 \( (p = 0.101) \), and a significant difference between RF-L0 and RF-L50 \( (p = 0.026) \), RF-L5 and RF-L50 \( (p = 0.012) \). In the second step of the statistical analysis, a two-factor within-subject repeated-measures ANOVA was used to analyze the influence of the contraction level of
Fig. 4 Average time courses of behavior across all participants for each condition during the ramp-hold period (N=20). The blue line means exerted force/EMG activities of the right hand. The Magenta line means exerted force/EMG activities of the left hand. **a** Average force of both hands for each condition. The horizontal axis depicts time during movement. The vertical axis denotes the values of the force. The shaded areas represented maximum and minimum range of the mean force of exerted force of each participant across all the participants at every sampling point. **b** Average EMG activities of both hands for each condition across all participants. The horizontal axis depicts time during movement. The vertical axis denotes the values of the EMG activities.

Fig. 5 Average force RMSE and the results of statistical analysis for each condition across all the participants (N=20). The horizontal axis depicts each condition. The vertical axis denotes the values of force RMSE. Error bar means standard deviation. **a** The mean force RMSE for conditions RF-L0, RF-L5 and RF-L50. **b** The mean force RMSE for conditions RF-L5, R-L5, RF-L50 and R-L50. * refers to p<0.05 with Holm–Bonferroni correction for post hoc test, vfb means visual feedback for the right hand, str means strength level of the left hand.
left-hand muscles and visual feedback for the right hand on the EMG_CV. The ANOVA results showed that the visual feedback does not significantly influence the EMG_CV ($F = 1.159$, $df = 1$, $p = 0.295$). The contraction level of left-hand muscles had a significant influence on the EMG_CV ($F = 22.661$, $df = 1$, $p < 0.001$). The interaction effect between visual feedback $\times$ contraction level of
left-hand muscles had no significant difference on EMG_CV ($F = 2.587, df = 1, p = 0.124$) (Table 2).

**Graph Theory-Based Measure**

Global and local efficiency were averaged across all 20 participants in theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz) and gamma (31–45 Hz) bands during each condition (Fig. 7). Further, we applied the statistical analysis to the following steps. The purpose of statistical analysis for graph theory-based measures was to determine whether significant differences occurred in the network of the whole cortical oscillatory in different motion conditions. In the first step of the statistical analysis, the global efficiency and local efficiency of the whole brain were averaged across 20 participants for conditions RF-L0, RF-L5 and RF-L50. The ANOVA results showed that global efficiency had significant difference in theta band ($F = 7.692, df = 1.027, p = 0.011$), alpha band ($F = 15.222, df = 1.022, p = 0.001$), beta band ($F = 4.550, df = 1.045, p = 0.044$) and gamma band ($F = 7.180, df = 1.049, p = 0.014$) between conditions RF-L0, RF-L5 and RF-L50. Further post hoc analysis showed differences were significant between conditions RF-L0 and RF-L5 ($p = 0.037$), RF-L0 and RF-L50 ($p = 0.034$) on global efficiency in theta band (Table 1). Post hoc analysis showed differences were significant between conditions RF-L0 and RF-L5 ($p = 0.004$), RF-L0 and RF-L50 ($p = 0.002$), RF-L5 and RF-L50 ($p = 0.042$) on global efficiency in alpha band (Table 1). Post hoc analysis showed difference was significant between conditions RF-L0 and RF-L5 ($p = 0.034$) on global efficiency in gamma band (Table 1). Besides, the ANOVA results showed that local efficiency had no significant difference in beta band ($F = 2.250, df = 1.065, p = 0.148$) and gamma band ($F = 3.037, df = 1.085, p = 0.094$) between conditions RF-L0, RF-L5 and RF-L50, rather than in theta band ($F = 7.599, df = 1.055, p = 0.011$) and alpha band ($F = 16.464, df = 1.038, p = 0.001$). Further post hoc analysis showed differences were significant between conditions RF-L0 and RF-L5 ($p = 0.036$), RF-L0 and RF-L50 ($p = 0.035$) on local efficiency in theta band (Table 1). Post hoc analysis showed differences were significant between conditions RF-L0 and RF-L5 ($p = 0.003$), RF-L0 and RF-L50 ($p = 0.001$) on local efficiency in alpha band (Table 1).

In the second step of the statistical analysis, a two-factor within-subject repeated measures ANOVA was used to analyze the influence of the contraction level of left-hand muscles and visual feedback for right hand on the mean theta, alpha, beta and gamma bands. The ANOVA results showed that the visual feedback significantly influenced the global efficiency in theta band ($F = 6.846, df = 1, p = 0.017$), alpha band ($F = 33.905, df = 1, p < 0.001$) rather than in beta band ($F = 0.042, df = 1, p = 0.841$) and gamma band ($F = 0.020, df = 1, p = 0.889$). The contraction level of left-hand muscles had significant influence on the global efficiency in alpha band ($F = 11.322, df = 1, p = 0.003$) rather than in theta band ($F = 0.711, df = 1, p = 0.410$), beta band ($F = 0.245, df = 1, p = 0.626$) and gamma band ($F = 0.728, df = 1, p = 0.404$) (Table 2). The ANOVA results showed that the visual feedback significantly influenced the local efficiency in theta band ($F = 4.450, df = 1, p = 0.048$), alpha band ($F = 51.166, df = 1, p < 0.001$) rather than in beta band ($F = 0.058, df = 1, p = 0.812$) and gamma band ($F = 0.063, df = 1, p = 0.804$). The contraction level of left-hand muscles had significant influence on the local efficiency in alpha band ($F = 9.625, df = 1, p = 0.006$) rather than in theta band ($F = 0.503, df = 1, p = 0.487$), beta band ($F = 0.933, df = 1, p = 0.346$) and gamma band ($F = 0.086, df = 1, p = 0.772$) (Table 2).

The interaction of visual feedback × contraction level of left-hand muscle was not significant on theta global efficiency ($F = 0.106, df = 1, p = 0.748$), theta local efficiency ($F < 0.001, df = 1, p = 0.987$), alpha global efficiency ($F = 3.052, df = 1, p = 0.097$), alpha local efficiency ($F = 3.040, df = 1, p = 0.097$), beta global efficiency ($F = 0.172, df = 1, p = 0.683$), beta local efficiency ($F = 0.677, df = 1, p = 0.421$), gamma global efficiency ($F = 0.055, df = 1, p = 0.818$) and gamma local efficiency ($F = 0.698, df = 1, p = 0.414$).

**Discussion**

We investigated the influence of manipulating visual feedback and contraction level of one hemisphere hand muscles related to sustaining force output, neuromuscular activity and cortical oscillatory processes during voluntary movement of the hand. We obtained three new results. First, the elimination of visual feedback for the right hand significantly decreased force accuracy in the right hand. Movement error decreased in unimanual task compared with bimanual task. Besides, moderate isometric contraction of left-hand muscle induced a significant increase in force RMSE and EMG_CV compared with a weak isometric contraction of left-hand muscle. Second, EMG_CV decreased in the unimanual task compared with the bimanual task of moderate isometric contraction of left-hand muscle. In addition, global and local efficiency of the network was larger in unimanual task compared with the bimanual task in the theta and alpha band. Besides, global efficiency of the network was larger in the unimanual task compared with the bimanual task of weak isometric contraction of left-hand muscle in gamma band. Furthermore, moderate isometric contraction of left-hand muscle induced a significant decrease in global efficiency of network in alpha band compared with a weak isometric contraction of left-hand muscle. Third, the existence of visual feedback resulted in decreased global
Fig. 7 Average global efficiency and local efficiency in different bands and the results of statistical analysis for each condition across all the participants (N=20). The horizontal axis depicts each condition. The vertical axis denotes the values of the global or local efficiency. Error bar means standard deviation. * refers to p < 0.05 with Holm–Bonferroni correction for post hoc test. vfb means visual feedback for the right hand, str means strength level of the left hand. The mean global efficiency in the a theta band, e alpha band, i beta band and m gamma band for conditions RF-L0, RF-L5 and RF-L50. The mean global efficiency in the b theta band, f alpha band, j beta band and n gamma band for conditions RF-L5, R-L5, RF-L50 and R-L50. The mean local efficiency in the c theta band, g alpha band, k beta band and o gamma band for conditions RF-L0, RF-L5 and RF-L50. The mean local efficiency in the d theta band, h alpha band, l beta band and p gamma band for conditions RF-L5, R-L5, RF-L50 and R-L50.
efficiency and local efficiency of the network of theta and alpha bands in the whole brain when compared to eliminate visual feedback. These observations were not found in beta and gamma bands, suggesting a frequency-dependent nature to the changes in the brain network. These findings indicated that theta and alpha-band oscillations coordinate to accurate hand movement.

**Effects of Visual Feedback on Force Output and Neuromuscular Activity**

In the current study, visual information was used to manipulate movement accuracy. Compared with the elimination of the visual feedback, the existence of visual feedback increased the force accuracy. Chung et al. (2017) conducted elbow flexor and extensor neuromuscular activity during ballistic movements, the study separated movement error rates using low and high visual gain. Compared to the low visual feedback, high visual gain significantly decreased the error and was associated with the alpha band, beta band and gamma band desynchronization between parietal and contralateral sensorimotor cortex (Chung et al. 2017). Bagci et al. (2012) found that visual feedback enhances performance and may modulate primary motor cortex excitability in stroke patients during finger flexion or extension. Based on previous studies, we extend the elbow activity or one-hand motion into bimanual hand movement to investigate the effect of visual feedback.

We found that movement error of right-hand muscle decreased in the unimanual task compared with the bimanual task. Similar results were found in the study of Smits-Engelsman et al. (2004), they found that the error of force increased in the bimanual task compared with the unimanual task. Besides, moderate isometric contraction of left-hand muscle induced a significant increase in force RMSE compared with a weak isometric contraction of left-hand muscle. These results suggested that co-contraction may increase the involvement of the antagonistic muscle, this process could recruit noise, thus, bring about extra movement disturbances.

EMG steadiness is an essential ability for the mobility of daily activities. EMG steadiness is caused by several factors such as aging, muscle contraction level and the use of unilateral or bilateral hand (Tracy and Enoka 2002; Long et al. 2016; Ushiyama et al. 2017). In the present study, EMG_CV decreased in the unimanual task compared with the bimanual task of moderate isometric contraction of left-hand muscle. Besides, moderate isometric contraction of left-hand muscle induced a significant increase in EMG_CV compared with a weak isometric contraction of left-hand muscle. However, EMG steadiness was not influenced by visual feedback of the right hand, besides, no significant difference was found between the unimanual task and bimanual task of weak isometric contraction of left-hand muscle. The reason could be that the influence of visual feedback and the contraction level of left hand between the unimanual task and the bimanual task of weak isometric contraction of the left-hand muscle on rFDI steadiness are weak when compared with EMG variability. Thus, subtle factors-dependent variables may be submerged in EMG random oscillations.

**Brain Network Efficiency and Task Performance**

We found that the brain network in theta and alpha band had significantly decreased global efficiency and local efficiency with visual feedback, suggesting that theta and alpha band of the brain network bears the load with visual feedback of the right hand during the steady-hold period. The functional network has been dynamically reorganized in different tasks, such as visual gain, visual feedback, finger movement and motor learning (Bedard and Sanes 2014; Archambault et al. 2015; Mehrkanoon et al. 2016; Ushiyama et al. 2017). A network system with a low local efficiency indicates a looser substructure connection of the network. Conversely, when local efficiency is higher, network topology is more robust in local information processing even if existed in inefficient or damaged neurons (Wang et al. 2010; Yu et al. 2011). Thus, the obtained results suggest that the brain is less robust in tasks with visual feedback compared to the tasks without visual feedback. This may be accounted for that network topology of tasks with visual feedback are more complex compared with tasks without visual feedback, which participants should pay more attention to adapt the external factors in bimanual movement. Global efficiency quantifies the information transferring at a macroscopic level. High global efficiency has advantages in minimizing noise, shortening the time delay of signal transfer and increasing the synchronization of the network in network system (Wang et al. 2012). In the current study, significant differences existed in global efficiency in conditions that whether visual feedback existed or not for the right hand. Global efficiency of the network was associated with widespread cortical regions responsible for visual input. This suggested that the neural processes may organize sparser neuronal assemblies with visual feedback. Tasks with visual feedback involve a feedforward and backward process to improve fine movement response. In addition, increased visual feedback could add the load of the brain compared with tasks without visual feedback due to the attenuated feedback processes. Besides, visual feedback participated in the long-distance feedback projections to visual areas from the top areas of the hierarchical model (Clavagnier et al. 2004), this process could improve the transfer time of information thereby decreasing the efficiency of the network. The lower efficiency means the longer transfer and process time. Generally, longer time paid to the task results in better performance and vice versa (Nasir et al. 2017). These results indicated the complex the
tasks were, the greater load the brain undertake, the greater
time of the brain cost, the lower local and global efficiency
were. Stanley et al. (2015) found that local efficiency was
significantly decreased in working memory compared with
resting state, global efficiency was decreased relatively when
compared with resting-state during the working memory
tasks, they also found that the better the performance of old
participants were, the lower global efficiency was. Lou et al.
(2015) found that the performance was negatively corre-
lated with local efficiency and global efficiency in healthy
participants.

Local efficiency was decreased during visual feedback
compared with no visual feedback in the theta band. Theta
band has shown to be bound up with sensorimotor integra-
tion (Zarka et al. 2014). Local efficiency of brain network
represents brain segregation (Bullmore and Sporns 2009).
Porter et al. (2019) conducted a sensorimotor task that
involved three tasks with five difficulty levels: a graded
mental task only, a graded physical task only and a graded
mental task and physical task simultaneously, they found
in the former three difficulty level the segregation property
of functional network increased during mental task only
and combined mental and physical task in the theta band,
decreased in the last two grades due to the increased task
difficulty. They analyzed the frontal area, the present study
extended the region to the whole brain. Therefore, we sug-
gested that the decrease local efficiency in the theta band
during visual feedback compared with no visual feedback is
associated with increased task difficulty.

Global efficiency was decreased during visual feedback
compared with no visual feedback in the theta band. Theta
band serves as the underlying physiological component
related to global oscillatory synchronisation course con-
necting multiple brain areas (Zarka et al. 2014). Rey et al.
(2014) applied single-neuron and local field potential tech-
nology to demonstrate that theta locking embodies a global
activation in visual recognition task. Global efficiency of
brain network represents brain integration (Bullmore and
Sporns 2009). Tamburro et al. (2020) conducted a flight
simulation under three incremental difficulty levels in 2D
and 3D surroundings. They found global and local efficiency
tended to decrease in theta and alpha band during the 3D
task compared with the 2D task because the 3D environ-
ment requires more visual information than 2D environment.
With the increase of task load, the global efficiency and local
efficiency tended to decrease in the theta band and alpha
band (Zhang et al. 2017). Therefore, we suggested that the
decrease global efficiency in the theta band during visual
feedback compared with no visual feedback is associated
with more visual input and task load.

Local efficiency was decreased significantly during
visual feedback compared with no visual feedback in the
alpha band. Alpha oscillation plays an important part in
suppressing irrelevant brain areas and neural activity to
adjust performance (Uusberg et al. 2013). Dai et al. (2017)
found segregation property of brain functional network
decreased significantly during 2-back working memory
compare with 0-back working memory, they suggested
that the reduction of functional segregation property in the
alpha band network be due to the higher task load. Moreo-
ver, alpha oscillation is related to attention and vigilance
(Knyazev et al. 2004). Therefore, the change of alpha func-
tional network may due to the level of attention towards
the task. Ghaderi et al. (2019) found decreased functional
segregation property during mathematical solving condition
compared with rest condition, but not in the theta band, they
suggested that the reduction of functional segregation prop-
erty in the alpha band due to the higher task load and arousal
level. Therefore, we suggested that the decrease of local effi-
ciency in the alpha band during visual feedback compared
with no visual feedback in the right hand is associated with
more task load and vigilance.

Global efficiency was decreased significantly during
visual feedback compared with no visual feedback in the
alpha band. Previous studies showed that decreased alpha
oscillatory facilitates neuronal processing (Haengens et al.
2011) and decreased coherence characterized by high effort
in the movement-related task (di Fronso et al. 2018). Moreo-
ver, Tamburro et al. (2020) conducted a cycling task that
was divided into six graded intervals: baseline period, ini-
tial period, intermediate period, final period, active pattern
and passive pattern, they found global efficiency tended to
decrease in the alpha band in stage 3 compared with stage
1 and 2 during the cycling task. In stage 3 the participants
performed the highest sustainable effort. Global efficiency
of brain network decreased in stage 3 because the partici-
pants performed the highest sustainable effort. Therefore,
we suggested that the decrease of global efficiency in the
alpha band during visual feedback compared with no visual
feedback in the right hand is associated with high load.

**Effects of the Level of Isometric Contraction on Neural Activity**

In this study, unilateral isometric contraction of right-hand
muscle induced a significant increase in the global and local
efficiency of the network in theta and alpha bands compared
with a week (5% of MVC) and moderate (50% of MVC)
isometric contraction of left-hand muscle. Besides, unilat-
eral isometric contraction of right-hand muscle induced a
significant increase in global efficiency of the network in
gamma band compared with a week (5% of MVC) isomet-
ritic contraction of left-hand muscle. Alpha band serves as
a sensitive function in detecting changes during force gener-
ation (Abdul-latif et al. 2004). Previous studies showed that
the EEG-EEG coherence and EEG spectral power decreased
during bilateral activity as compared with unilateral force in the alpha band (Long et al. 2016). The effect of the level of isometric contraction on the efficiency of the alpha-band is similar to the effect of the visual feedback. Local efficiency of alpha-band increase in unilateral isometric of right hand compared with bimanual movement may due to the decreased task load and attention (Dai et al. 2017; Ghaderi et al. 2019). Global efficiency of alpha-band increase in unilateral isometric of right hand compared with bimanual movement may due to the decreased task load (Tamburro et al. 2020). Besides, intermittent theta burst stimulation to the left dorsal premotor cortex can enhance primary motor cortex excitability during bimanual visuomotor training (Neva et al. 2015). Gamma band may connect neural clusters that encodes multiple sensory modulations (Lebar et al. 2017). In the bilateral task, divided attention may participate in the bimanual movement. When unilateral isometric contraction takes place, global and local efficiency increased, because divided attention was limited. When the left hand was performing weak and moderate isometric contraction, global and local efficiency decreased, because attention was affected. Besides, this mechanism is sensitive to global efficiency. In this study, we found that weak (5% of MVC) isometric contraction of right-hand muscle induced a significant increase in the global efficiency of the network in alpha band compared with moderate (50% of MVC) isometric contraction of left-hand muscle. Thus, the present study suggests a broad-band network regulation across theta, alpha and gamma bands during sustain force output.

There are several limitations in the current analysis. Firstly, the relatively small number of participants and the epoch number restrict its statistical results in this study. Secondly, the constructed brain functional network considers linear dependency between a pair of electrodes and the obtained connections are directionless. It is impossible to deduce the underlying information propagation in detail. Therefore, we intend to adopt the non-linear and directional measures in our future study to delineate the detailed information loop under visually guided hand movement. Thirdly, we analyze young, highly educated and healthy participants. We are not sure that findings of this study can employed in other populations, such as children, older people, uneducated or poorly educated people, patients with stroke. In the following study, we intend to study patients with stroke during visuomotor tasks.

Our research explores the neurophysiology evidence between brain oscillations network and online visuomotor performance. In this research, movement errors were reduced with visual feedback. Movement error decreased in the unimanual task compared with the bimanual task. Besides, moderate isometric contraction of left-hand muscle induced a significant increase in force RMSE and EMG_CV compared with a weak isometric contraction of left-hand muscle. In addition, EMG_CV decreased in the unimanual task compared with the bimanual task that moderate isometric contraction of left-hand muscle. Moreover, global and local efficiency of the network was larger in the bimanual task compared with the bimanual task in the theta and alpha band. Besides, global efficiency of the network was larger in the unimanual task compared with the bimanual task of weak isometric contraction of left-hand muscle in gamma band. Furthermore, moderate isometric contraction of left-hand muscle induced a significant decrease in global efficiency of the network in alpha band compared with a weak isometric contraction of left-hand muscle. We also observed changes in decreased global and local efficiency of the network in theta and alpha band in the whole brain with visual feedback, suggesting that specific band suppression of oscillation network occurred in the theta and alpha band during the steady-hold period. Further, we suggest that theta and alpha band synchronous networks in the whole brain were associated with the attentional allocation and visual information to optimize motor performance for visual information during motor corrections. These findings have a considerable impact on rehabilitation training of virtual reality auxiliary equipment and provide new insight on neurological disorders that cause movement errors that are required for accurate motor training.

Authors’ Contributions JW and YZ design and perform of experiment; JG analyzed data; JG and TL interpreted results of experiment; JG prepared figures and drafted manuscript; JG and AQ modified the grammar; JG, TL, LL, AQ and JW edited and revised manuscript. All authors contributed to the article and approved the submitted version.

Funding The study was financially supported by the National Natural Science Foundation of China (Grant No. U1913216), National Key Research and Development Program Project (Grant No. 2021YFC2400203).

Availability of Data and Materials The datasets generated and/or analysed during the current study are not publicly available due data privacy but are available from the corresponding author on reasonable request.

Declarations Competing interest The authors declare that they have no competing interests.

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