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Short Report

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Dynamic causal modeling for EEG during complex laparoscopic skill acquisition

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ABSTRACT

Fundamentals of Laparoscopic Surgery (FLS) is a prerequisite for board certification in general surgery in the USA. It includes a motor skills portion with five psychomotor tasks of increasing task complexity: (i) pegboard transfers, (ii) pattern cutting, (iii) placement of a ligating loop, (iv) suturing with extracorporeal knot tying, and (v) suturing with intracorporeal knot tying. Learning these tasks typically relies on extensive practice [1]. Nemani et al. [2] showed that the wavelet coherence based functional connectivity from functional near-infrared spectroscopy (fNIRS) data between the medial prefrontal cortex and the supplementary motor area (SMA) was lower for experts than novices during FLS pattern cutting task. Here, SMA is known for the plasticity of interhemispheric connectivity involving sensorimotor network [3] relevant in learning bimanual laparoscopic tasks; however, transcranial direct current (tDCS) of SMA resulted in more variability during FLS pegboard transfers than bilateral primary motor cortex tDCS. Here, it is essential to differentiate tDCS effects on the pre-SMA from SMA proper in the SMA complex during laparoscopic skill acquisition due to differences in their fiber tracts [4] and their relevance to motor task complexity. Prior work using fNIRS-based activation during most complex FLS suturing task with intracorporeal knot tying [5] showed the involvement of premotor/frontal module [4] related Brodmann areas (BA), shown in Figure 1c, including ventrolateral PFC (VLPFC; BA: 44, 45, 47), frontopolar (FP; BA: 10), dorsolateral PFC (DLPFC; BA: 9, 46) as well as a part of the orbitofrontal cortex (OFC; BA: 11) on the lateral brain surface in addition to SMA complex. However, the effective connectivity of this cognitive-motor control network was not investigated based on dynamic causal modeling (DCM) [6], where the temporal resolution of electroencephalogram (EEG) can capture fast interactions expected via short frontal lobe connections [4]. Therefore, our research aimed to identify hidden brain networks during FLS suturing with intracorporeal knot tying skill acquisition using DCM of EEG.

Methods: The study was approved by the Institutional Review Board of the University at Buffalo. Eight right-handed novice subjects (age: 22-32 years) performed the FLS suturing task for the first time using an FLS-certified physical trainer box. The experimental setup is shown in Figure 1a. The session consisted of a block design of 2 min rest and a FLS suturing task (stimulus) period – 3 min for the experts and 10 min for the novices. EEG imaging was conducted at 500Hz using wireless LiveAmp (Brain Products, USA) during three repeated blocks of rest and stimulus for each subject. Our EEG electrode montage consisted of 32 channels that covered the prefrontal and sensorimotor brain areas, as shown by Figure 1b.

Data processing was conducted using the open-source EEGLab toolbox [7] in Matlab (Mathworks Inc., USA). The raw data were first downsampled to 250Hz. Then, a high-pass filter was applied to the data at 1-Hz. Then, the line noise was removed using the “CleanLine” function. Then, we applied the function “clean_rawdata()” to reject bad channels and interpolated the removed channels (maximum 5). We then referenced the data to average and applied “clean_rawdata()” function to perform Artifact Subspace Reconstruction (ASR). ASR processing is essential to remove movement-related artifacts where the optimal ASR parameter is between 20 and 30, balancing between removing non-brain signals and retaining brain activities [8]. Then, we re-referenced the data to average. We then performed independent component (IC) analysis (ICA) using “runica” function and localized the dipoles using “dipfit” function [9]. We used the default head model settings in the EEGLab toolbox [7] for the dipole localization. The brain-related ICs were identified based on the dipole location in the brain and then were subjected to DCM in the open-source SPM12 toolbox [10]. DCM is an approach to quantify effective connectivity between brain areas where we were interested in elucidating the cognitive-motor control network in novices based on our prior work [11]. From Kamat et al. [11], Figure 2a shows the directed functional network based on time-varying Granger causality using EEG channel data (same dataset and preprocessing as described above in EEGLab) that was significantly ($p < 0.05$) different between experts and novices.

Results: In Figure 2a, the left PFC(LPFC) node includes EEG channels overlying the left DLPFC and VLPFC and then vice versa for the right PFC (RPFC) node. Also, the SMA node includes the EEG channels overlying the SMA complex, while the LM1 node includes EEG channels overlying left sensorimotor areas, including the primary motor cortex, premotor cortex, and parietal cortex and vice versa for the RM1 node. We investigated all possible networks of superficial (cortical) IC sources related to the nodes in Figure 2a using DCM. Figure 2b shows the posthoc selection [12], where the left frontoparietal network (FPN) was found to be most evident during the whole task duration (constant IC model) in novices. Here, IC related to the frontal theta activity that was localized at the left DLPFC while the IC localized at the centroparietal regions is postulated to be the sensorimotor μ rhythm and the Figure 2c shows the effective connectivity found from DCM. The Figure 2d shows the ICs at the medial frontal cortex (left panel) and parietal lobe (right panel); however, they were not consistent [13] across novices.

Discussion: We showed the feasibility of an EEG-based DCM approach to elucidate the brain networks during complex FLS suturing task in novices that was found left lateralized [4]. We found that the novices mostly had the node at the pre-SMA while experts showed more SMA proper node – needs further investigation. Then, the relevance of the DLPFC node in all the novices can be related to attentional control (FPN) necessary during skill learning [14]. Ashcroft et al. [15] found that tDCS of DLPFC (BA 9) improved performance score in an open surgery knot-tying task. However, that surgical task can be considered less complex than the FLS suturing task in this study. Here, we postulate based on prior work [16] that transcranial alternating current stimulation targeting the left FPN may be more effective for FLS suturing task with neuroimaging-guided transcranial electrical stimulation [5].

Competing interests: The authors declare no competing interests.

Figure 2. (a) Directed functional network based on time-varying Granger causality using EEG channel data. LPFC: left prefrontal cortex. RPFC: right prefrontal cortex. SMA: supplementary motor complex. LM1: left sensorimotor area. RM1: right sensorimotor area. (b) Cortical independent components (ICs) found in novices (N=8). (c) Dynamic causal modeling results using cortical ICs where left frontoparietal network was found to be most active in novices during the whole task duration (connection strength shown by the color bar). (d) Illustrative dipole locations at medial frontal cortex (left panel) and parietal lobe (right panel).

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