

Graph Theoretical Analysis of EEG-Based Functional Connectivity During Visuo-Haptic Interactions in Virtual Environments

Ha Yeon Yoon

Department of Software Convergence
Kyung Hee University
Yongin, South Korea
alice6114@khu.ac.kr

Tae Seong Kim

Department of Software Convergence
Kyung Hee University
Yongin, South Korea
ahgmfrghvk@khu.ac.kr

Ju Yeon Jung

Department of Metaverse
Kyung Hee University
Yongin, South Korea
jungju1130@khu.ac.kr

Jung Geun Ahn

Department of Metaverse
Kyung Hee University
Yongin, South Korea
wingker2@khu.ac.kr

Tack Woo

Department of Metaverse
Kyung Hee University
Yongin, South Korea
twoo@khu.ac.kr

Won Hee Lee*

Department of Software Convergence
Kyung Hee University
Yongin, South Korea
whlee@khu.ac.kr

Abstract—The integration of multisensory, particularly the fusion of visual and tactile inputs, plays a crucial role in human perception and environment interaction. Despite its importance, the neural mechanisms underlying visuo-haptic integration remain poorly understood. This study investigates the brain's functional connectivity during visuo-haptic tasks within virtual environments using electroencephalography (EEG) and graph theoretical analysis. We collected EEG data from participants engaged in tasks requiring simultaneous processing of visual and tactile stimuli. Functional connectivity was constructed from the EEG signals, and we analyzed key graph theoretical metrics to characterize the network's properties. Specifically, in the tactile-only condition, we observed decreased global efficiency and small-worldness in both beta and theta frequency bands, accompanied by an increase in characteristic path length. In addition, strength, local efficiency, and clustering coefficient were diminished in the tactile-only condition, compared to conditions with visual input. However, we found no significant differences in brain network topology across different tactile feedback modalities. These results provide novel insights into how the brain's dynamic coordination of multisensory inputs and establish a solid foundation for future investigations of visuo-haptic processing using graph theoretical approaches.

Keywords—EEG, visual, haptic, graph theory, functional connectivity

I. INTRODUCTION

The integration of visual and haptic information is fundamental to human perception and interaction with the environment. Visuo-haptic interaction, which combines visual input with tactile sensation and proprioception, enables us to perform complex tasks ranging from simple object manipulation to sophisticated motor skills [1]. This multisensory integration process relies on intricate neural networks that coordinate information from different sensory modalities, yet the underlying mechanisms of these networks remain incompletely understood.

Recent advances in neuroimaging and electrophysiological techniques have opened new avenues for investigating brain function and connectivity. Electroencephalography (EEG), with its high temporal resolution, offers a unique opportunity to investigate the rapid dynamics of neural processes during visuo-haptic interaction [2, 3]. Moreover, the application of graph theory to neuroscience has emerged as a powerful approach to

characterize the complex network properties of the brain, providing insights into its functional organization and information processing capabilities [4]. This approach represents brain activity as a network where EEG electrodes serve as nodes, and functional connections between brain regions form edges. Various network metrics, such as clustering coefficient, strength, and efficiency, can then be calculated to characterize the network's properties [5].

While previous studies have investigated either visuo-haptic integration or graph theoretical analysis of EEG data separately [6-9], there remains a significant gap in research that combines these approaches to elucidate functional connectivity patterns during visuo-haptic tasks within virtual environments. This study aims to bridge this gap by employing graph theoretical analysis of EEG-based functional connectivity to examine the neural mechanisms involved in visuo-haptic interactions. Specifically, we focus on characterizing the functional connectivity networks associated with visuo-haptic interactions using EEG and graph theoretical approaches. Our goal is to examine how network properties change under varying conditions of haptic feedback processing. Furthermore, we investigate the frequency-specific changes in network topology during visuo-haptic tasks, providing insights into the underlying neural mechanisms that facilitate sensory integration.

II. METHODS

A. Participants

Thirteen healthy volunteers participated in this study. All participants were right-handed and had normal or corrected-to-normal vision. None of the participants reported a history of neurological or psychiatric disorders. Written informed consent was obtained from all participants before the experiment. The study protocol was approved by the Kyung Hee University Institutional Review Board (IRB: #KHGIRB-23-427).

B. Experimental Setup and Protocol

The study used a mixed-methods approach to investigate visuo-haptic integration mechanisms across both virtual and physical environments. The experimental protocol was structured into two primary phases: (1) virtual reality (VR) interactions, which systematically evaluated the influence of



Fig. 1. Experimental setup where participants use a haptic glove in a virtual environment while wearing a head-mounted display (HMD).

varying haptic feedback modalities in virtual environments and (2) real-world interactions, which examined the reciprocal relationship between visual input and haptic feedback under controlled conditions. In the VR phase, participants engaged with virtual interfaces while receiving different levels of haptic feedback, allowing for the assessment of how tactile sensations influence user performance and perception in virtual spaces. The real-world phase investigated the complementary aspect by manipulating visual input conditions during physical interactions, enabling the examination of how visual information modulates haptic perception and motor control. Both experiments utilized a numeric keypad typing task as the standardized interaction paradigm. All participants completed the conditions in a predetermined sequence to maintain consistent experimental progression and control for order effects.

During the VR interactions, participants were equipped with a head-mounted display (HMD; Meta Quest 3) and performed typing operations on virtual keypads within a carefully designed VR environment. The experimental protocol comprised four distinct input methods, each testing different aspects of haptic interaction: (i) natural hand tracking without haptic feedback, which relied solely on the HMD's built-in hand tracking capabilities (*NoHaptic*); (ii) standard VR controller interaction using the Meta Quest 3 controller, providing basic vibrotactile feedback (*BasicHaptic*); (iii) enhanced tactile feedback delivered through specialized haptic gloves (bHaptics TactGlove), which provided localized vibrotactile sensations to fingertips during key presses (*EnhancedHaptic*); and (iv) a synchronized digital twin configuration where participants' real-world typing actions were precisely mirrored in the virtual environment, creating a direct correspondence between physical and virtual interactions (*TwinHaptic*).

During the real-world interactions, participants performed standardized typing tasks on physical numeric keypads under three distinct visual conditions to examine the relationship between visual input and tactile perception. The conditions were (i) tactile-only condition (*TO*), where participants were blindfolded to isolate pure tactile feedback without visual input; (ii) mixed-reality condition (*MR*), where participants viewed a VR environment precisely synchronized with physical objects through digital twin technology, enabling the manipulation of visual representation while maintaining consistent tactile feedback; and (iii) natural-vision condition (*NV*), where participants had unobstructed visual access to the physical keypad, serving as a baseline for natural visuo-haptic integration.

C. EEG Data Acquisition

EEG data were continuously recorded using an Emotiv EPOC+ wireless headset equipped with 14 Ag/AgCl electrodes positioned according to the International 10-20 system (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4). Reference electrodes were placed at P3 and P4

and electrode impedances were maintained below 5 k Ω , with saline solution applied as needed to ensure optimal signal conductivity.

Raw EEG signals were digitized at a sampling rate of 128 Hz with a 16-bit resolution. Signal quality was continuously monitored through the Emotiv SDK interface, with markers automatically inserted to indicate any periods of poor signal quality (impedance >10 k Ω or signal artifacts). Sessions were paused and electrodes readjusted if signal quality dropped below acceptable thresholds. EEG data were collected continuously during each condition, resulting in a total of 91 EEG recordings across all conditions (13 participants $\times$ 7 conditions).

D. EEG Preprocessing

EEG data preprocessing was performed using the open-source EEGLAB toolbox in MATLAB environment (R2024a). The preprocessing pipeline followed a systematic approach to ensure data quality and reliability. Initially, electrical line noise was removed using a 60 Hz notch filter with a 2 Hz bandwidth. The data then underwent rigorous channel quality assessment, where channels were identified as problematic if they met any of the following conditions: flatline periods exceeding 5 seconds, z-scored noise-to-signal ratio above a threshold of 4, or inability to be predicted from neighboring channels for at least 80% of the recording duration [10]. To address signal drift, a high-pass filter ranging from 0.25 to 0.75 Hz was applied, followed by re-referencing to the average reference to minimize reference bias. Artifact removal was accomplished through independent component analysis (ICA) using extended infomax algorithm, where components representing non-neural activity (such as eye movements, muscle artifacts, or electrical noise) were automatically identified and removed if their artifact probability exceeded 80%. Subsequently, any previously identified bad channels were reconstructed through interpolation based on the signal patterns of surrounding good channels. After completing the preprocessing pipeline, 10 datasets were excluded from further analysis due to persistently poor signal quality identified during the quality assessment process. For subsequent analyses, the EEG data were categorized into conventional frequency bands: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-50 Hz).

E. Functional Connectivity Construction

We constructed undirected, weighted functional connectivity by calculating coherence between all pairs of EEG channels at each frequency band. Coherence quantifies the degree of synchronization between two signals, ranging from 0 (no synchronization) to 1 (complete synchronization). For each frequency band, we generated a 14×14 coherence matrix, resulting in 81 coherence matrices per frequency band. Across all frequency bands, we obtained a total of 405 functional connectivity matrices. Each matrix element A_{ij} represents the coherence value (weight) between channel i and channel j .

F. Graph Theoretical Analysis

To analyze the topological characteristics of the brain networks during visuo-haptic tasks, we computed eight graph theoretical measures [11]: characteristic path length (L), global efficiency (GE), small-worldness (SW), strength (S), betweenness centrality (BC), eigenvector centrality (EC), local efficiency (LE), and clustering coefficient (CC). These

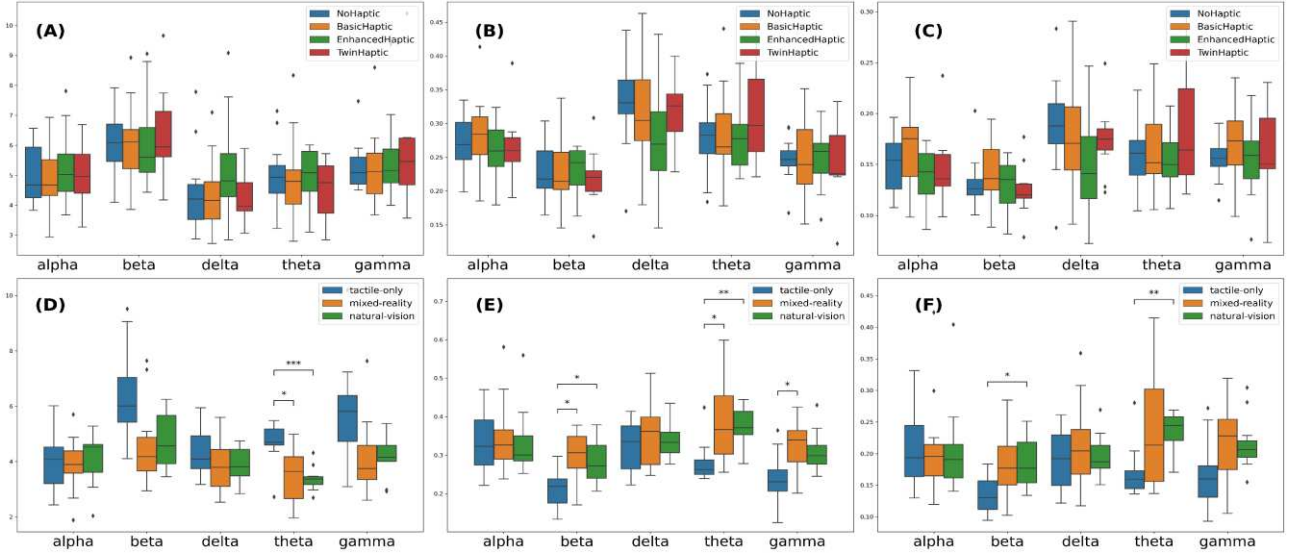


Fig. 2. Global graph theoretical measures across different visuo-haptic tasks for each frequency band: (A) characteristic path length, (B) global efficiency and (C) small-worldness during the VR interactions as well as (D) characteristic path length (E) global efficiency and (F) small-worldness during the real-world interactions.

metrics were calculated using the Brain Connectivity Toolbox [5].

G. Statistical Analysis

To compare graph theoretical measures between visual and tactile tasks, we conducted a one-way analysis of variance (ANOVA), followed by *post-hoc* pairwise comparisons using Games-Howell tests. The false discovery rate (FDR) correction was applied to control for multiple comparisons [12]. Statistical significance was determined at a *p*-value threshold of 0.05.

III. RESULTS

A. Global Network Measures

Fig. 2 shows three global network measures (characteristic path length, global efficiency, and small-worldness) during the VR and real-world interactions. During the real-world interactions, in the both theta and beta bands, both global efficiency and small-worldness were significantly reduced in the TO condition compared to the MR and NV conditions. In the theta band, we found that characteristic path length was significantly higher in the TO condition compared to both the MRI and NV conditions in the theta band. However, no significant differences were found in any of the global measures for the VR interactions.

B. Local Network Measures

Graph theoretical analysis revealed significant differences in local network measures (CC, LE, BC, EC, and S) across different experimental conditions. Most notable differences were observed in the beta and theta frequency bands during real-world interactions (Fig. 3). In Fig. 3(A), the TO condition exhibited distinct patterns of network topology compared to the MR condition. For example, in the beta band, the TO condition showed significant decreases in CC, LE, and S in the temporal (T8), parietal (P8), and frontal (F7, F3, FC6, FC5) regions. However, an increase in EC was observed in the alpha band in the TO condition. In Fig. 3(B), compared to the NV condition, the TO condition showed lower CC, LE, and S in the frontal (F7, F4, FC5, FC6), temporal (T7, T8), and occipital (O1) regions in the theta band. Similarly, in the beta band, the TO condition displayed reduced CC, LE, and S in

the frontal (FC5, FC6), temporal (T7, T8), and parietal (P8) regions, along with higher BC in the occipital (O1) region. Similarly, in the gamma band, reduced strength was found in the frontal (FC6) region was observed in the TO condition.

In the analysis of VR interaction, minimal differences were observed between different haptic feedback methods, with one notable exception: in the delta band, higher EC in the temporal region (T7) during the *EnhancedHaptic* condition was observed compared to the *TwinHaptic* condition, suggesting potentially enhanced sensory processing with specialized haptic feedback.

IV. DISCUSSION

Our findings suggest that the visual input plays a crucial role in shaping brain network dynamics during visuo-haptic interactions. The significant decrease in global efficiency and increase in characteristic path length in the theta and beta frequency bands during the TO condition indicate reduced information processing efficiency and increased neural transmission delays. The lower small-worldness during the TO condition implies a less efficient and specialized network, suggesting that the brain may rely on less efficient processing strategies when visual input is absent. Interestingly, the type of haptic input did not significantly impact brain network dynamics in VR, suggesting that the brain may process tactile information similarly regardless of the specific input device.

In the TO condition, we found decreased CC and LE in the parietal (P8) and temporal (T8) areas in the beta band, compared to the MR condition. Also, the TO condition showed reduced CC, LE, and S in the frontal (FC5, FC6), temporal (T7, T8), and parietal (P8) in the beta band, compared to the NV condition. Similarly, in the theta band, lower CC, LE, and S were identified in the temporal (T7, T8), frontal (F7, F4, FC5, FC6), and occipital (O1) regions in the TO condition. These findings highlight the importance of these regions in visual processing and suggest that their network activity diminishes in the absence of visual input [13].

Our results showed that different haptic input methods have a similar impact on brain network dynamics during VR interactions, suggesting that the specific type of haptic input

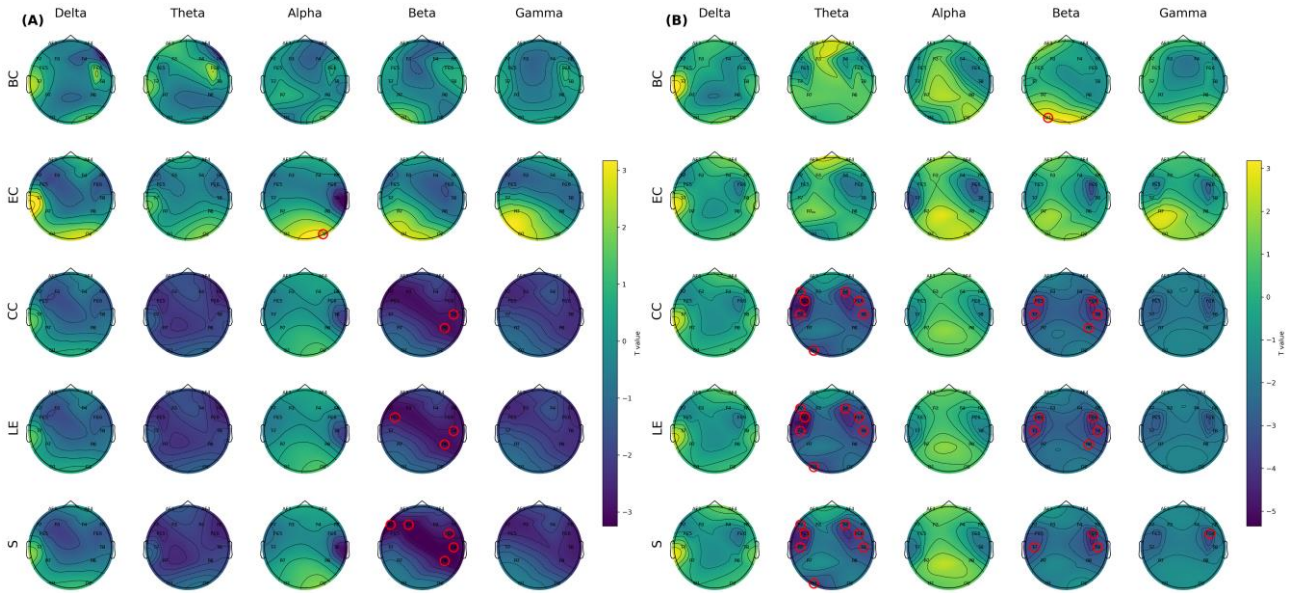


Fig. 3. Topographical maps showing the statistical comparisons of local network measures for each frequency band: (A) t-values representing the differences in local measures between the tactile-only and mixed-reality conditions and (B) t-values representing the differences in local measures between the tactile-only and natural-vision conditions. BC = betweenness centrality; EC = eigenvector centrality; CC = clustering coefficient; LE = local efficiency; S = strength.

did not appear to significantly affect the overall brain network topology. This implies that both haptic gloves and controllers can effectively provide tactile feedback that is perceived similarly to real-world touch.

V. CONCLUSION

This study investigated the topological characteristics of EEG-based functional brain networks during varied visual and tactile input conditions. Through graph theoretical analysis of brain network connectivity, we found distinct patterns of brain network topology across different experimental conditions. In real-world interactions, significant differences were observed in beta and theta frequency bands during the tactile-only condition compared to conditions with visual input. Notably, the presence of visual input was associated with increased node centrality primarily in the frontotemporal regions, likely reflecting enhanced multisensory processing and integration. However, the specific effects of different tactile feedback modalities, including direct hand tracking, controller, and haptic glove, on brain network topology was less pronounced. This finding suggests that current haptic technology may simulate natural tactile sensations in virtual environments, achieving neural responses similar to bare-hand interactions.

Future research should focus on the neural mechanisms underlying visuo-haptic integration by investigating the role of specific brain regions and the temporal dynamics of brain network connectivity. Additionally, exploring the impact of varied haptic feedback parameters (intensity, duration, frequency) on brain network dynamics could provide further insights into the neural basis of multisensory integration.

ACKNOWLEDGMENT

This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP), funded by the Korea government (MSIT) under grants RS-2024-00509257 (Global AI Frontier Lab), IITP-2024-RS-2024-00438239 (ITRC, Information Technology

Research Center), and RS-2022-00155911 (Artificial Intelligence Convergence Innovation Human Resources Development, Kyung Hee University).

REFERENCES

- [1] K. Kahol *et al.*, "Evaluating the role of visio-haptic feedback in multimodal interfaces through EEG analysis," *Augmented Cognition: Past, Present and Future*, vol. 290, 2006.
- [2] H. Alsuradi, C. Pawar, W. Park, and M. Eid, "Detection of tactile feedback on touch-screen devices using eeg data," in *2020 IEEE Haptics Symposium (HAPTICS)*, 2020: IEEE, pp. 775-780.
- [3] H. Wu *et al.*, "Evaluation of motor training performance in 3D virtual environment via combining brain-computer interface and haptic feedback," *Procedia Computer Science*, vol. 107, pp. 256-261, 2017.
- [4] E. Bullmore and O. Sporns, "Complex brain networks: graph theoretical analysis of structural and functional systems," *Nature reviews neuroscience*, vol. 10, no. 3, pp. 186-198, 2009.
- [5] M. Rubinov and O. Sporns, "Complex network measures of brain connectivity: uses and interpretations," *Neuroimage*, vol. 52, no. 3, pp. 1059-1069, 2010.
- [6] R. Chavarriaga, X. Perrin, R. Siegwart, and J. d. R. Millán, "Anticipation-and error-related EEG signals during realistic human-machine interaction: A study on visual and tactile feedback," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012: Ieee, pp. 6723-6726.
- [7] P. Arpaia, D. Coyle, F. Donnarumma, A. Esposito, A. Natalizio, and M. Parvis, "Visual and haptic feedback in detecting motor imagery within a wearable brain-computer interface," *Measurement*, vol. 206, p. 112304, 2023.

- [8] S. Micheloyannis, E. Pachou, C. J. Stam, M. Vourkas, S. Erimaki, and V. Tsirka, "Using graph theoretical analysis of multi channel EEG to evaluate the neural efficiency hypothesis," *Neuroscience letters*, vol. 402, no. 3, pp. 273-277, 2006.
- [9] W. De Haan *et al.*, "Functional neural network analysis in frontotemporal dementia and Alzheimer's disease using EEG and graph theory," *BMC neuroscience*, vol. 10, pp. 1-12, 2009.
- [10] C. Gil Ávila *et al.*, "DISCOVER-EEG: an open, fully automated EEG pipeline for biomarker discovery in clinical neuroscience," *Scientific Data*, vol. 10, no. 1, p. 613, 2023.
- [11] W. H. Lee, E. Bullmore, and S. Frangou, "Quantitative evaluation of simulated functional brain networks in graph theoretical analysis," *NeuroImage*, vol. 146, pp. 724-733, 2017.
- [12] Y. Benjamini and Y. Hochberg, "Controlling the false discovery rate: a practical and powerful approach to multiple testing," *Journal of the Royal statistical society: series B (Methodological)*, vol. 57, no. 1, pp. 289-300, 1995.
- [13] J. Aru and T. Bachmann, "Occipital EEG correlates of conscious awareness when subjective target shine-through and effective visual masking are compared: Bifocal early increase in gamma power and speed-up of P1," *Brain research*, vol. 1271, pp. 60-73, 2009.