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ORIGINAL ARTICLE

Exploring Brain Functional Connectivity in Hand Motion and Motor Imagery through fNIRS Signals: A Graph Theory Approach

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Abstract

Purpose: Functional Near-Infrared Spectroscopy (fNIRS) is a valuable and cost-effective neuroimaging technique, particularly in the context of sensorimotor tasks and its applications in brain-computer interface (BCI) research. While numerous studies have explored brain functional connectivity during sensorimotor tasks, they have often primarily focused on electrical brain activity. In this study, we present a signal processing algorithm utilizing fNIRS-HbO2 data to identify active brain regions involved in both actual motor execution and motor imagery within a motor imagery task.

Materials and Methods: Our algorithm incorporates several key steps: firstly, the application of wavelet transform to eliminate noise and preprocess the fNIRS signal. Subsequently, we employ correlation analysis to extract functional connectivity matrices for both motor execution and motor imagery. Finally, we compute global efficiency (GE) values, a significant graph theory parameter, to analyze network properties. Additionally, we investigate the small-world network characteristics within the connectivity matrices and classify motor execution and motor imagery using a t-test.

Results: To gather data, we recorded 20-channel fNIRS signals, measuring changes in HbO2 concentration in the motor cortex, from 12 healthy participants at a sampling frequency of 10 Hz. Our findings not only confirm the presence of small-world network properties in the correlation matrices but also reveal that meaningful classification between motor execution and motor imagery of both right and left hands occurs when we select the top 40% of the strongest connections between channels. Furthermore, the results indicate a tendency towards stronger connectivity between channels in the left hemisphere.

Conclusion: In summary, our study demonstrates that brain networks are organized as small-world networks during sensorimotor tasks and underscores the prominent role of the dominant hemisphere in executing these tasks.

Keywords: Functional Near-Infrared Spectroscopy; Motor Imagery; Graph Theory; Small World Network; Functional Connectivity.

DOI:

1. Introduction

Advancements in neurological studies have unveiled the intricate interactions and functional connectivity within brain networks during various cognitive activities [1]. These interactions play a pivotal role in understanding the brain's capacity to integrate information across its diverse regions and are at the forefront of contemporary neuroscience research. Functional Near-Infrared Spectroscopy (fNIRS) has emerged as a powerful and non-invasive tool in exploring brain functional connectivity [2]. Its resilience to electrical noise and ease of application have made it an attractive choice for researchers aiming to unravel the dynamics of brain networks. Importantly, fNIRS allows for the measurement of changes in oxyhemoglobin and deoxyhemoglobin concentrations, enabling the assessment of metabolic activity within brain cells [2]. The versatility of fNIRS applications is reflected in their usage in a diverse range of cognitive tasks, including motor imagery [3-4], music imagery [5-8], object rotation [9], motion detection [10], and mental arithmetic [11-16]. These studies have provided valuable insights into brain activity and connectivity patterns during various cognitive challenges. Graph theory has emerged as a valuable approach for analyzing brain networks, offering insights into their structural organization and connectivity patterns [17]. Previous studies employing graph theory have shed light on critical aspects of functional connectivity within the brain. Dadgostar *et al.* utilized this methodology to explore functional connectivity within the prefrontal cortex during cognitive tasks, revealing bilateral connectivity between hemispheres [1]. Einalou *et al.* investigated functional connectivity disparities between healthy individuals and patients with schizophrenia during cognitive challenges [18]. Additionally, studies have harnessed graph theory to assess brain functional connectivity under varying cognitive loads, highlighting fluctuations in global efficiency [17]. The impact of mental fatigue on the interaction between the Prefrontal Cortex (PFC) and Motor Cortex (MC) during simulated driving has also been scrutinized using fNIRS [19]. Motor imagery, a cognitive process simulating motion mentally before its execution, holds significant importance in cognitive and neurological rehabilitation [20]. This cognitive function has attracted attention in recent studies that have explored the parallels between Motor Execution (ME) and Motor Imagery (MI) [21-28]. An *et al.* employed fNIRS to illustrate that motor imagery activates the primary motor cortex [24]. Additionally, functional Magnetic Resonance Imaging (fMRI) studies have investigated functional connectivity in various brain regions during motor imagery tasks [29].

Despite substantial research in these domains, there remains a dearth of studies focusing on metabolic activities and functional connectivity during motor imagery tasks. This study aims to bridge this gap by comprehensively evaluating and comparing brain functional connectivity during the execution of motor tasks and motor imagery involving both right and left-hand fingers using fNIRS signals. Data collected during the tasks are meticulously preprocessed using the wavelet transform, and functional connectivity information from the motor cortex (MC) is extracted using graph theory [30-32]. The overarching objective is to contribute to a deeper understanding of the metabolic activities and functional connectivity that underlie cognitive tasks and motor activities. The primary innovation of this study lies in its holistic examination of brain functional connectivity during motor imagery tasks, filling a significant research gap in the field [30-32]. By employing fNIRS and graph theory, we aim to provide a comprehensive understanding of the metabolic activities and connectivity dynamics underlying cognitive tasks and motor function. Our research promises to shed new light on the intricate processes governing motor imagery and cognitive activities, thus contributing to a deeper understanding of the human brain's functional architecture and potential applications in neurological rehabilitation. In synthesizing a comprehensive understanding of brain network interactions, fNIRS applications, graph theory, and motor imagery, this study aspires to elucidate the intricate processes that govern cognitive tasks and motor function.

2. Materials and Methods

2.1. Subjects and Protocol

The data for this study were acquired using the OxyMonfNIRS (Artinis) system, within the facilities of the National Brain Mapping Laboratory. The participant cohort was composed of 12 healthy, right-handed individuals, each with a mean age of 25 ± 5 years, and no history of psychiatric or neurological conditions. The study population consisted of 5 men and 7 women, yielding a gender distribution of 42% men and 58% women.

Prior to data collection, all participants underwent a formal informed consent process and received detailed instructions on the task to be performed. A visual representation of the data recording protocol can be found in Figure 1.

As shown in Figure 1, first the baseline signal was recorded for 60 seconds, and then four task blocks including motion left (ML), motor imagery left (MIL), motion right (MR), and motor imagery right (MIR) were performed by the participants. The duration of each task block was 20 seconds and each of them was repeated 4 times during data recording. Also, a rest time of 40 seconds was considered between the two task blocks. The total time of the data record process for each participant was 17 minutes and the task was performed in a dark and quiet room. During the task, fNIRS signals were recorded and saved from 20 channels in the motor part of the volunteers' brains at a sampling frequency of 10 Hz as shown in Figure 2. The optodes were strategically positioned at specific anatomical locations in the motor cortex of the volunteers' brains. These locations were selected based on established neuroimaging principles and the nature of the motor-related tasks under investigation. Specifically, the optodes were placed over the primary motor cortex, which is typically located in the precentral gyrus of the cerebral cortex, in order to capture relevant brain activity associated with motor tasks. This precise placement ensured the recording of fNIRS signals from the primary motor cortex, a region known for its involvement in motor control and execution. Including the mention of the primary motor cortex provides clarity and specificity in the methodology.

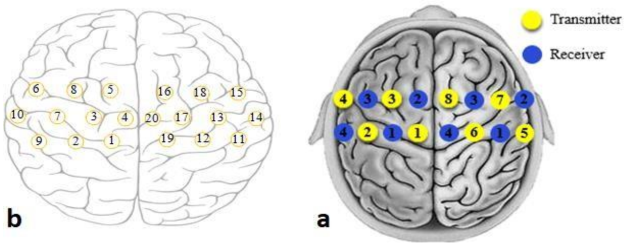

Figure 2. a. Location of fNIRS signal recording optodes on the motor area of the brain (yellow dots indicate light transmitters and blue dots indicate light receivers), **b.** Number of fNIRS channels in the motor area of the brain

2.2. Signal Processing Algorithm

In this study, the processing of fNIRS signals was performed using a detailed procedure, as depicted in Figure 3. The complexity arises from the fact that fNIRS signals, like other physiological signals, are susceptible to various sources of interference such as motion artifacts, ambient noise, physiological noise, and device noise. To extract the desired brain activity-related signals from these interferences, noise removal methods are crucial. Prior research, as referenced in [1, 17, 33, 34], has established that fNIRS signals predominantly contain brain activity-related information within the frequency range of 0.003-0.08 Hz. However, several physiological interferences, such as cardiac activity (0.8-1.5 Hz), respiratory activity (0.2-0.5 Hz), and changes in arterial blood pressure (0.1 Hz), can introduce unwanted noise into the fNIRS signal [1]. To enhance the study's ability to investigate brain function via fNIRS signals, it is imperative to mitigate the effects of these physiological interferences, as highlighted in references [35-37]. To address this issue, we employed the Discrete Wavelet Transform (DWT), which is well-documented for its effectiveness in denoising fNIRS signals. The fNIRS signal was first decomposed into 11 levels. As a preprocessing step, the approximation coefficients of level 11 were zeroed out to eliminate the DC signal, and the detail

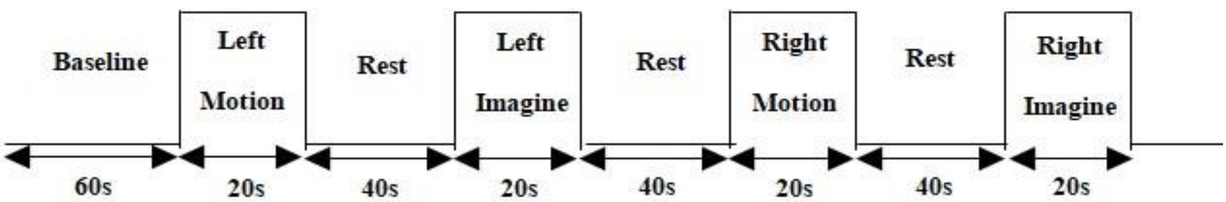

Figure 1. Protocol for recording motion and motor imagery of the right and left-hand's fingers

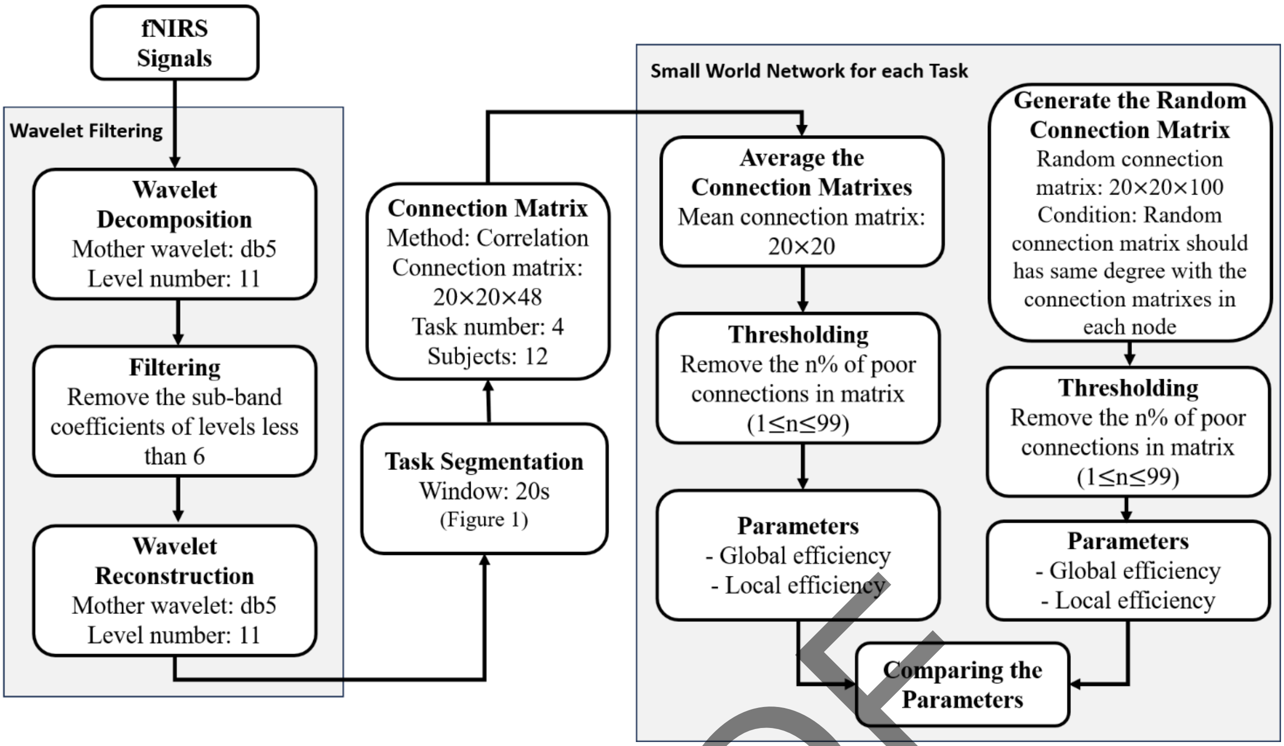

Figure 3. Proposed diagram for processing fNIRS signals

coefficients of the first six levels were set to zero to extract the frequency content between 0.003 and 0.08 Hz. Subsequently, we used the inverse wavelet transform to reconstruct the output signal within the specified frequency range (0.003-0.08 Hz). This approach, referenced in [1, 17, 38, 39, 34], allowed us to effectively remove unwanted noise and enhance the quality of the fNIRS signal for further analysis.

Since the recorded signals include four blocks of left-hand motion, left-hand motor imagery, right-hand motion, and right-hand motor imagery, for the signal segmentation, the parts related to each task block were separated from the whole signal according to the protocol in Figure 1. According to the sampling frequency, the total data length for each task block is equal to 200 samples.

The correlation coefficient has been used to evaluate brain functional connectivity based on graph theory.

In our study, we used Pearson's correlation coefficient (r) as a measure for the connectivity matrix. The formula for Pearson's correlation coefficient is as follows (Equation 1):

$$R=\frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2(y-\bar{y})^2}} \qquad (1)$$

here:

- X and Y represent the time series data of the two regions being correlated.
- $\bar{X}$ and $\bar{Y}$ denote the means of the respective time series data.

Pearson's correlation coefficient is commonly used to quantify the linear relationship between two variables and is suitable for measuring connectivity between regions of interest in fNIRS data.

By creating a functional connectivity matrix for each task block, connectivity between all relevant channels was obtained. Each channel corresponds to a node in the graph. Therefore, according to Equation 1, for a graph with N nodes, a connectivity matrix N × N is obtained whose array values are between -1 and +1 [24].

$$C_{ij}=\begin{bmatrix} C_{11} & \cdots & C_{1N} \\ \vdots & \ddots & \vdots \\ C_{N1} & \cdots & C_{NN} \end{bmatrix} \qquad (2)$$

Where C_{Task} is the functional connectivity matrix related to each task block and the values of the correlation coefficient C_{ij} are between two channels (nodes) i and j.

In this study, the graph matrix is calculated based on the correlation between each pair of channels. Hence, this matrix represents the metabolic activity of networks in the sensorimotor part of the brain, which are recorded by 20 fNIRS channels. Given that the values of correlation coefficients are between -1 and 1, the proximity of the absolute value to 1 means that there is stronger connectivity between networks.

After extracting the functional connectivity matrix by calculating the correlation coefficients between the channels, to evaluate the functional connectivity in the networks between the channels for four states of ML, MIL, MR, and MIR, two graph-related features were investigated under small-world conditions.

2.2.1. Global Efficiency

Global efficiency is obtained by calculating the inverse of the path length. In a high-performance network, short connectivity paths can be identified among different node pairs [25] (Equation 3):

$$Global\ Efficiency = \frac{1}{N(N-1)} \sum_{i \neq j \epsilon G} \frac{1}{L_{ij}} \tag{3}$$

N is the number of nodes and Lij is the path length between nodes i and j.

2.2.2. Local Efficiency

$$Local\ Efficiency\ (G) = \frac{1}{n} \sum_{nodes} E_{glob}(G_i) \tag{4}$$

G_i is a subgraph of G consisting of the neighbors of node I (Equation 4).

GE and LE were calculated for all individuals in all 4 task states and finally averaged.

2.2.3. Small-World Network

A small-world network is a type of graph in which many nodes are not neighbors, but the neighbors of each node are most likely interconnected. As a result, it is possible to get from one node to another with a small number of steps. In fact, networks are called small-world networks whose usual distance between two random vertices (L) is a coefficient of the logarithm of the total number of nodes in the network (N) (Equation 5).

$$\propto \log \tag{5}$$

However, the clustering coefficient is not small in these networks. In other words, nodes tend to form clusters. In social network science, these features represent the small-world phenomenon in which strangers are connected by a short chain of acquaintances [26, 27].

In this study, to investigate the small-world nature of the given network, the mean correlation matrix of fNIRS signal components in each task state was obtained and then the weak connectivity was removed with a step of 1%, respectively. In each of the resulting matrices with different percentages of the strongest connectivity, graph parameters were calculated and then averaged. In contrast, for each of the 100 random connectivity matrices that were similar to the original graph in terms of the number of nodes and degree of a node, the proposed approach was implemented. The main graph was then compared with GE and LE for an average of 100 random graphs to investigate the small-world network condition, GE and LE with different percentages of the strongest connectivity. Then, the appropriate threshold was selected from the percentage of strong connectivity that met the small-world network condition.

In a small-world network, there is always the following Equation 6.

$$LEreal > LErandom\ ,\ GEreal < GErandom \tag{6}$$

2.2.4. Statistical Test

T-test is the simplest form of testing parametric hypotheses for real data. The use of a t-test allows investigating the difference in the mean of the two statistical populations. In fact, this test allows evaluation of the difference between the two statistical populations according to the mean. It should be noted that the t-index is usually used when the variance of the population is unknown. The number *t* is calculated by the following Equation 7:

$$t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{\sigma_x^2}{n_x} + \frac{\sigma_y^2}{n_y}}} \tag{7}$$

Where $\bar{x}$ and $\bar{y}$ are the averages of the two statistical populations, and σ and n are the standard deviation and the number of samples of statistical populations, respectively. Finally, by calculating the degree of freedom (df), the calculated t number is compared with the table of t-distribution. If the calculated t is higher than the table of t-distribution, the test is significant [28] (Equation 8).

$$df = n - 1 \tag{8}$$

In this study, a t-test with a p-value of <0.05 was used for GE for right-hand motion and right-hand motor imagery, and left-hand motion and left-hand motor imagery to determine only a percentage of strong connectivity. A significant difference was between motion and motor imagery. Accordingly, the channels in which the specified percentage of strong connectivity related to each other in the connectivity matrix should first be identified. Then, the strongest connectivity of the channels in each state in parts of the brain was shown. Also, the channels related to each other both in motion and motor imagery were shown.

3. Results

3.1. Small World

As shown in Figures 4 and 5, according to Equation 5, the small-world network condition should be met for almost all thresholds. These Figures show the GE and LE values of the main and random graphs for the strongest network connectivity, respectively, in the thresholds between zero and 0.5. They also show that at these thresholds of GE of the main graph was lower than the random graph, but the values of LE were inversely higher in the main graph. Thus, these conditions not only prove that the main graph is the small-world network but also show that the strongest connectivity can be considered to reduce the calculation load by up to 60%. On the other hand, as shown in Figure 6, the GE ratio of the main graph to the random graph reached its lowest value around the threshold of 0.1, indicating the largest difference between the GE of the main graph and the random graph. However, as shown in Figure 7, the evaluation of the difference in the distribution of GE values of the main graph between the two classes ML-MIL and MR-MIR using t-test analysis shows that the distribution of GE values with the threshold of 0.3-0.5 on average showed a significant difference ($p < 0.05$). As shown, in both MR-MIR classes, GE distributions around the threshold of 0.1 were also significant. However, it can be said that for both ML-MIL and MR-MIR classes, the threshold of 0.4 had the largest difference in the distribution of GE.

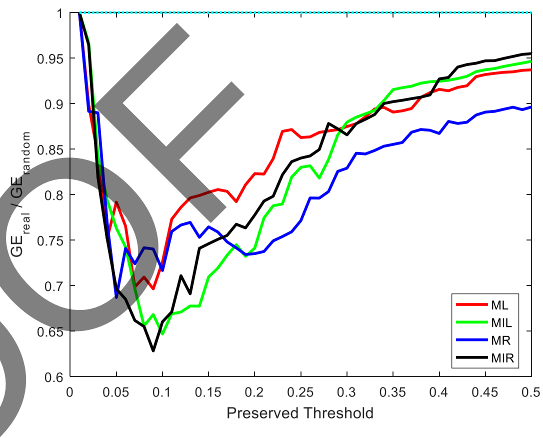

Figure 4. GE of the main and random graphs with different thresholds for each of the task states of ML, MIL, MR, and MIR. Bold lines represent main networks and dashes represent random networks

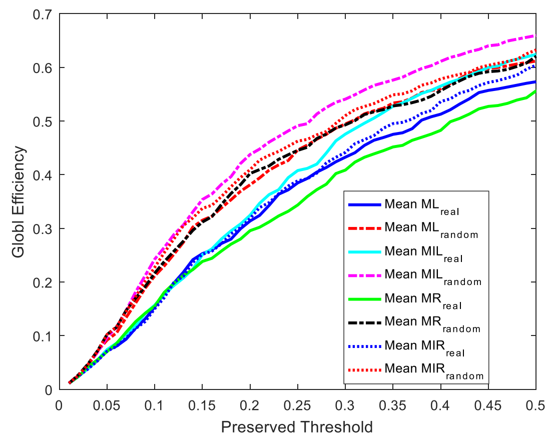

Figure 5. LE of the main and random graphs with different thresholds for each of the task states of ML, MIL, MR, and MIR. Bold lines represent main networks and dashes represent random networks

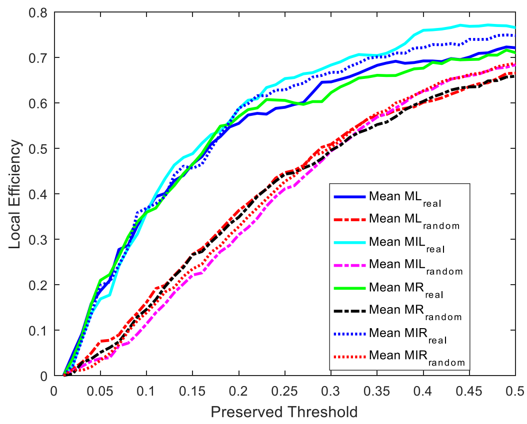

Figure 6. GE ratio of the main graph to random graph with different thresholds for each of the task states of ML, MIL, MR, and MIR

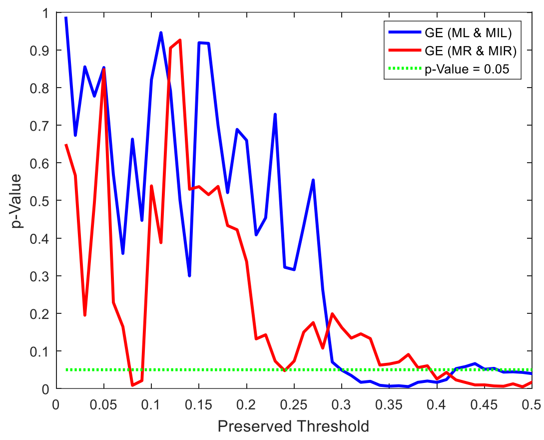

Figure 7. Evaluation of the difference in the distribution of GE values of the main graph in two classes of ML-MIL and MR-MIR using t-test analysis

The nodes that were related to each other in most of the participants are shown in Table 1. In fact, these nodes were related to each other in at least 7 participants and were considered as graph nodes with the strongest connectivity. Figure 8 shows four graphs of ML, MIL, MR, and MIR. As shown in Table 1 and Figure 8, the strongest connectivity was in the fNIRS channels in the left hemisphere.

4. Discussion

Brain functional connectivity, particularly in the context of sensorimotor activity, is a complex and essential aspect of human physiology, attracting significant attention in various studies, notably in the field of Brain-Computer Interfaces (BCIs). Researchers in the field of neuroscience employ a comprehensive approach that dissects brain network activities at specific signal recording points. These recording points capture diverse aspects of brain function, such as electrical and metabolic activity, with each point representing an information node. The application of graph theory enables researchers to analyze the characteristics of this data, providing insights into the functional connectivity of different brain regions during various cognitive sensorimotor tasks.

In this study, the primary objective was to investigate the functional connectivity of individuals' brains using graph theory, specifically during motor imagery tasks with functional Near-Infrared Spectroscopy (fNIRS) signals. To ensure the quality of the fNIRS data, a wavelet transform-based filter, in combination with correlation analysis, was employed for signal preprocessing. Global Efficiency (GE) emerged as a central graph parameter for assessing small-world network properties and detecting significant differences between motion and motor imagery states, as determined through t-tests. The results emphasized the suitability of GE for revealing significant disparities between the two groups.

Table 1. 40% of nodes with the strongest connectivity among all participants in the main graph

Task	Channel Connection
ML	(1,2)(1,3)(1,5)(1,8)(1,20)(2,3)(2,7)(2,20)(3,5)(3,6)(3,8)(3,10)(3,16)(3,20)(5,8)(6,9)(6,10)(7,20)(8,20)(12,17)
MIL	(1,16)(2,7)(2,20)(3,8)(3,16)(4,5)(4,16)(4,20)(6,7)(6,13)(7,8)(7,14)(9,10)(9,11)(9,12)(9,14)(12,17)(13,18)(15,18)(16,18)
MR	(1,3)(1,4)(1,5)(2,3)(2,7)(2,9)(3,4)(3,5)(3,6)(3,7)(4,5)(5,8)(6,7)(6,8)(6,9)(6,10)(7,8)(7,9)(7,13)(8,13)(9,13)(11,13)
MIR	(2,3)(2,18)(3,7)(3,8)(3,9)(3,18)(5,20)(6,7)(6,8)(7,8)(7,11)(9,10)(9,14)(14,15)(16,20)(17,18)

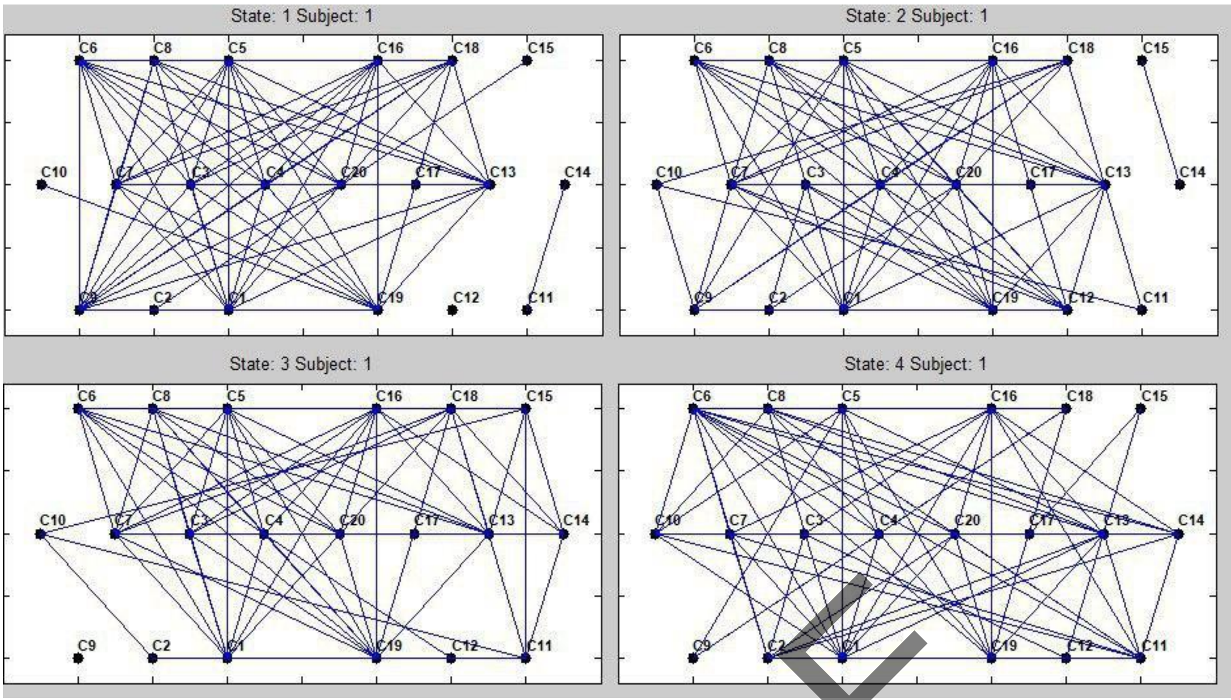

Figure 8. Four graphs related to four states of ML, MIL, MR, and MIR for subject 1

Furthermore, the study examined the Small-World Network (SWN) condition and identified the proportions of the strongest connectivity where GE exhibited significant differences, shedding light on the associated brain regions.

The selection of graph theory measures, including Global Efficiency (GE) and small-world-ness, was a deliberate choice guided by the study's specific research objectives. Graph theory offers a wide array of metrics tailored to analyze complex networks. In this case, the study focused on assessing the functional connectivity of brain networks, particularly within the sensorimotor region, recorded by 20 fNIRS channels. Global Efficiency (GE) was chosen due to its ability to gauge the efficiency of information transmission between network nodes, providing insights into overall network efficiency regarding information flow, a crucial aspect in the study of brain connectivity. The inclusion of small-world-ness was driven by its capacity to reveal network organization concerning information segregation and integration. This metric illuminated whether the network exhibited small-world network characteristics, a common feature in various biological networks, including the brain. Small-world-ness provided insights into the balance between local specialization and global information integration, aligning with the study's objectives.

The choice of the wavelet transform-based filter for fNIRS signal preprocessing was a well-founded decision, supported by previous studies [31, 35-37, 40-42]. The utilization of motor imagery tasks and graph theory for the investigation of brain functional connectivity represents a methodological innovation with several distinct advantages over previous approaches, as exemplified in [40, 43]. Notably, this approach offers a unique insight into the dynamic reconfiguration of brain networks during cognitive tasks. Unlike many traditional resting-state fMRI studies, which primarily capture spontaneous fluctuations in brain activity, motor imagery tasks provide a controlled cognitive context, allowing us to explore how the brain responds to specific cognitive demands and simulates motor actions mentally. This not only enhances our understanding of the neural mechanisms underpinning cognitive processes but also holds substantial clinical relevance, as cognitive rehabilitation and neurorehabilitation often involve motor imagery exercises. Furthermore, by applying graph theory to these data, we can comprehensively assess the topological organization of brain networks, uncovering properties such as small-world characteristics and efficiency. This detailed network analysis surpasses traditional seed-based or region-of-interest approaches, providing a holistic view of how brain regions communicate during motor imagery. Such insights can inform the development of tailored interventions for patients with motor-related disorders, such as stroke or Parkinson's disease, by optimizing brain network plasticity. Moreover, our methodology leverages advanced signal preprocessing techniques, as discussed in previous sections, to enhance data quality.

This filter effectively removed noise from fNIRS signals and specifically addressed motion artifacts. In contrast, the Independent Component Analysis (ICA) algorithm, although capable of isolating independent sources, was less suitable for removing physiological noise present in the signal background, making it less ideal for this study's goals.

The exploration of brain functional connectivity has been a recurring theme in various studies. Kim *et al.* [43] investigated changes in brain network connectivity during Motor Imagery (MI) tasks involving hand-finger movements. Xu [44] delved into the functional connectivity of the motor area in children with Down syndrome, comparing metrics such as GE and the shortest path length between patient groups and healthy individuals. This study, however, focused on assessing brain functional connectivity using motor imagery tasks and graph theory.

In contrast to fMRI-based studies, such as that by Hu *et al.* [29], which explored changes in brain network topology using graph theory and assessed parameters like GE and Local Efficiency (LE), this study found distinct results. While the previous study reported a significant difference in LE within the range of 0.1-0.2, no significant difference was observed for GE. In this study, the evaluation of GE for the ML-MIL and MR-MIR classes using t-tests revealed significant differences at thresholds of 0.4-0.5. Graphs constructed based on these thresholds provided valuable insights into brain network connectivity in the sensorimotor area during four task states. Additionally, the statistical analysis revealed that the nodes with the strongest connectivity were predominantly situated in the left hemisphere of the brain. This observation was consistent with the fact that all participants in the study were right-handed, suggesting stronger connectivity in the dominant hemisphere during cognitive tasks. These results aligned with a study by Chen *et al.* [45], which highlighted the need for different motor imagery-based strategies for right-handed and left-handed individuals.

In summary, this study demonstrated the utility of analyzing fNIRS signals using graph theory to investigate brain network connectivity during various sensorimotor tasks. The results provided valuable insights into the characteristics of these networks and their relevance to neuroscience and potential applications in neurorehabilitation and Brain-Computer Interfaces (BCIs).

5. Conclusion

In the light of the critical role brain functional connectivity plays in comprehending its intricate structure and diagnosing various disorders, it is prudent to expand upon this study by integrating other imaging modalities such as functional Magnetic Resonance Imaging (fMRI) and Electroencephalography (EEG). These complementary approaches can provide a more comprehensive view of brain network interactions and contribute to a more robust understanding of functional connectivity patterns.

While this study predominantly focused on Global Efficiency (GE) as a graph parameter, it is advisable to explore additional graph metrics and thresholds to determine the most suitable parameters for channel selection. A more comprehensive investigation could reveal nuanced insights into brain network connectivity and facilitate a more refined channel selection process, potentially improving the accuracy of connectivity analysis.

Moreover, this study was conducted with a relatively small sample size for evaluating fNIRS signals, which revealed that brain networks in the dominant hemisphere exhibit stronger connectivity. To enhance the generalizability of the findings, it is essential to conduct research with larger and more diverse statistical populations. Expanding the scope of research to encompass hybrid graph representations of electrical and metabolic activity across different cerebral hemispheres presents an exciting avenue for future studies.

The findings and methodologies presented in this study hold the promise of contributing to the betterment of individuals with disabilities, particularly in the context of neurorehabilitation and Brain-Computer Interfaces (BCIs). It is hoped that these research insights can pave the way for advancements in these areas, ultimately leading to improved therapeutic strategies and quality of life for those affected by neurological conditions.

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