Connectivity Analysis of Functional Brain Networks in Using Multi-modal Human-Computer Interaction

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Abstract

To develop next generation multi-modal computer-aided design systems, it is important to evaluate the relationships between the user dependent factors and the combined performance of man and machine. The purpose of this research is to investigate if users' cognitive activity would increase with the use of multi-modal input, speech and gestures by analysing EEG signals. Experiments are conducted, using traditional (keyboard and mouse) and multi-modal (speech and gesture) inputs. We used Normalized transfer entropy as a connectivity measure to find the information flow patterns. We constructed binary and weighted Functional Brain Networks to explore distinct and varied brain regions quantitatively. We found significant differences in cognitive activity between the traditional and multi-modal inputs. Our statistical analysis results state that the user's cognitive activity increase when a multi-modal input is used. The findings have implications for the development of multi-modal interfaces for 3D modelling.
Keywords: Multi-modal interface system, transfer entropy, functional brain networks, graph theory, EEG, 3D modelling.

1. Introduction

The advancements in virtual and augmented reality have presented the users the opportunity to use the multi-modal input rather than the traditional mouse and keyboard input. The multi-modal input is a vital part of smart phones, VR headsets, and game boxes as well as Computer-aided design (CAD), Computer-aided manufacturing (CAM) and Computer Aided Engineering (CAE) as a preferred option to design 3D objects. Multimodal inputs can be speech, touch, facial expressions, gestures, and handwriting [33]. The availability of multiple inputs improves the usability of Human-Computer Interaction (HCI) systems.

In this paper, we have analyse the cognitive activity and information flow patterns when participants are using the traditional unimodal versus multi-modal input to draw 3D objects. We have used transfer entropy (TE) of the EEG signals to analyze the connectivity between electrodes and then used the TE matrix to generate both binary and weighted functional brain networks (FBNs). We have used the graph theory methods to study characteristics the FBNs.

In this paper, we have answered the following research questions:

1. What are the differences in cognitive activity when using a multimodal system compared to the unimodal system?
2. Are there any differences in information flow patterns and cognitive activity in HCI using speech and gestures?

The remaining document is organized as follows: Section 2 contains the related work. The methodology of the experiment has been given in Section 3. Results and discussions are part of Section 4 and Section 5 that conclude the paper.

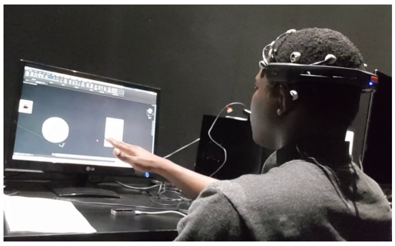
2. Related Work

The use of small-world properties of complex network metrics to understand brain networks has gained a rapid interest. The small-world properties have been found in games, control systems, and neural networks. The results from various studies reviewed in this paper indicate that the Functional Brain Networks (FBNs) constructed from neuroimaging data such as EEG, MEG, and fMRI has demonstrated small-world properties [24, 18]. A detailed analysis of the use of graph theory to understand cognitive activities was conducted by Bullmore and Sporns [7] and a systematical method to construct FBN from raw EEG data was proposed. Rubinov and Sporns reviewed applications of complex network measures along with the comparison of structural and functional brain networks providing an open-access toolbox for MATLAB to calculate the complex network measures.

Langer et al. [16] investigated the relationship between the intelligence and FBNs constructed from the EEG data and found a strong correlation between intelligence, clustering coefficient, and characteristic path length for the diagnosis of psychological disorders. Rubinov et al. [21] used weighted FBNs constructed from EEG data to see the differences in clinical and healthy samples during resting state and found significant differences in clustering coefficient, characteristic path length, and degree centrality similar to Jalili and Knyazeva [14]. De Haan et al. [10] examined the Alzheimer's Disease and dementia using EEG data and found significant loss of small-world network properties in alpha, beta and gamma band similar to ADHD and depression analysis which showed significant variations in small-world properties when compared to healthy persons in [1, 17].

In music perception, Fallani et al. [11] found that simple foot movement can alter connectivity patterns dramatically. By using graph theoretical measure, Wu et al. [32] showed that during music perception the clustering coefficient was larger, and the characteristic path length was smaller. They further demonstrated that the small-world network properties were related to the perception of music not sound. Transfer entropy was used to construct FBNs from EEG data [28]. Three different states were evaluated: resting, driving and driving with audio distraction. The results showed significant differences in connectivity density, motif, clustering coefficient and degree distribution across all three states. In a web search-based task analysis through FBN, maximum connectivity was observed in query formulation task [27].

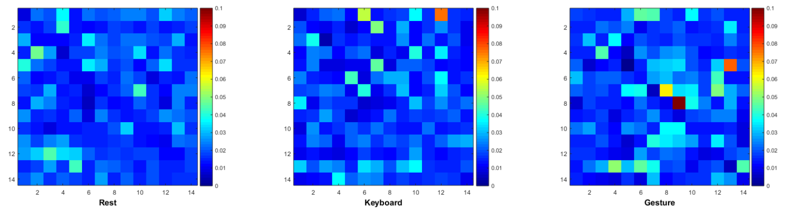
(a) Participant using keyboard and mouse to draw 3D object



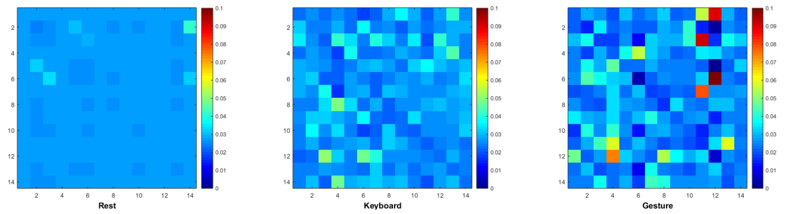
(b) Participant using speech and gesture to draw 3D object

Figure 1. Experimental setup with real time conditions

Graph-based methods have been applied by researchers to successfully study complex brain networks in recent years [28] and more specifically using both directional and undirected functional brain networks (FBN) [7, 29]. In research, directional FBN is preferred because it provides more prominent topological features by estimating the direction of information transfer between nodes (EEG electrodes) and thereby enabling more detailed analysis [19]. To construct an FBN using an EEG, a connectivity measure is used that can estimate the value of information transferred between nodes (electrodes). There are many linear and non-linear connectivity measures that have been used in the literature to construct the FBN such as mutual information, Entropy, correlations, and Granger causality [23]. Linear connectivity measures usually fail to



(a) User 2 (competent) (completed experiment in small span of time)



(b) User 12 (novice) (completed experiment in large span of time)

Figure 2. NTE connectivity matrices for two users during rest, keyboard and gesture drawing states

identify the non-linear behavior of the brain. Therefore, to analyze a highly non-linear EEG signal, non-linear measures are adopted by the researchers for the construction of FBNs [25].

2.1. Functional Brain Networks and Graph Theoretical Analysis

Transfer Entropy (TE) is also a popular measure to quantify information between two non-linear vectors. It can also determine the direction of information transfer between two variables [6] and therefore, is ideal for investigating information flow. TE uses the past activity of both variables to estimate the amount of activity of a system irrespective of interaction model. This property of TE allows the researchers to apply it to various applications such as identifying information transfer between auditory cortical data [13], localization of epileptic patients focus [8], the effect of heart rate on breath rate [22], and information flow patterns in various driving states [26]. In the research literature, TE has not been used to study user dependent differences. In this paper, we have used the Normalized Transfer Entropy (NTE) for calculating the connectivity matrix. Normalized transfer entropy (NTE) is calculated by dividing the difference of transfer entropy matrix (TE) from a shuffled version of that TE matrix by conditional entropy. The subtraction of shuffled TE overcomes the noise/bias of TE generated due to the finite and non-stationary data [30, 15, 5].

Functional Brain Networks (FBNs) are used to capture the information flow dynamics between EEG electrodes in relation to human brain [31]. EEG is a common tool to measure the brain activity as it is inexpensive, non-invasive and have a high temporal resolution. EEG has been used in many applications ranging from medical diagnostics, cognition to brain-computer interfaces [3]. The graph theory measures such as connectivity density, motif count, node strength, and clustering coefficient are used to estimate the cognitive activity of the user as these measures describe the strength of the network. The mean information flow is calculated by averaging the information passing through each electrode using the NTE matrix.

3. Methodology

3.1. A Multi-modal interface system

We have developed a multi-modal interface prototype (xDe-SIGN) that allows users to design objects in 3D, using AutoCAD commands as well as speech and gesture [2, 4]. The system used a microphone to collect speech input and a Leap motion sensor to collect gesture input in real time. Usually, in modeling software, there are two possible ways to manipulate the camera view: either using a mouse or the orbit. The orbit is the easiest way to move the camera by clicking directly on the cube. With speech, a user can move the camera using classical directions such as 'move camera vertically and horizontally' and 'zoom in and out'. Using gestures, the camera can be activated or deactivated: when the system detects a closed hand followed by an open hand, it activates or deactivates the camera.

To implement the design concept, a dll plugin for AutoCAD containing 4 main classes: MySpeech, LeapListener, MyMain, and MyDrawAutocad have been created. MySpeech starts the speech recognition function and sends an event when the speech is recognized. LeapListener first initializes the gesture recognizer and defines all the gestures to be recognized and sends an event when a gesture is recognized. MyMain receives the speech and gesture events, interprets them and sends the right command to AutoCAD. MyDrawAutoCad contains all the functions to draw or manipulate the object or the camera. For more information regarding the system see [2, 4]. Using the system participants achieved a task completion rate of above 90% with the upgrades but the precision is low depending on participants.

In this research, we analyzed the cognitive activity of the participants through EEG signals while using this multi-modal interface system. We have used a connectivity measure to estimate the information flow between electrodes and then used FBNs and graph theory-based methods to study the behavior. We apply TE to the analysis of information flow patterns of novice and competent user users. We have used normalized TE values to construct both binary and weighted directional FBNs. After constructing an FBN, we have applied graph theory measures and statistical analysis to quantify the information flow patterns.

3.2. Experimental Setup and Data Acquisition

The experiment was to design a 3D table with three parts: a base, a pillar, and a top in AutoCAD with two sets of inputs i.e. keyboard mouse and speech and gesture using xDeSIGN. In most EEG studies the number of participants varies from 5-20 [28, 20], in this study we used 12 participants. All of them were computer-science students at Macquarie University. The ages of the participants range from 21 to 30 years. Four of the participants were competent users of AutoCAD and 8 were novices. The experiment was approved (Approval no. 5201700784) by the Faculty of Science and Engineering Human Research Ethics Sub-Committee, Macquarie University.

Each subject was given a tutorial of 10 minutes before the experiment. A video log has been maintained for each subject and EEG signals were recorded. For the acquisition of EEG signals, we used an off-the-shelf research edition of the Emotiv EEG headset, which has 14 channels and record signals at a sampling rate of 128 Hz. The EPOC headset has 14 channels belongs to various brain regions: frontal and front-central: AF3, AF4, F3, F4, F7, F8, FC5, FC6; temporal: T7, T8; and the occipital and occipital-parietal: O1, O2, P7, P8. The electrode placement is based on the international 10-20 system. Emotiv Headset has limited electrodes with no electrodes in the central lobe (Pz, Cz, Fz). The manufacturer states that the signals from the neighboring electrodes are good enough to perform experiments and researchers have proved the capability of the headset in many applications [9]. The subjects were given an open-ended task in order to depict the real-world setting, which results in complex cognitive processing and analysis strategies. A picture of the experimental setup is shown in Fig. 1.

3.3. Experimental procedures

The process can be divided into 5 experimental procedures:

1. Information about the experiment was given to each subject along with the consent form.
2. The EEG headset was placed on the head of the subject and the experimenter made sure that all channels were in good contact with the skull. The subjects were asked to rest for two minutes with their eyes open, with hands on their laps, and after that, the subjects

were asked to start drawing using keyboard and mouse. This was called Resting state.
3. After the completion of the modeling task with keyboard and mouse, the participants were given instructions about the multi-modal interaction system.
4. After completing the task with speech and gesture inputs, subjects were asked to fill in a questionnaire about the experiment.
5. EEG data were filtered and for convenience, we named the first task (keyboard and mouse drawing) "Keyboard" and the second task (speech and gesture drawing) "Gesture" drawing state.

3.4. EEG Signal Pre-Processing

The EEG data of all the participants were used for the analysis. The preprocessing was done in MATLAB 2017b using the EEGLAB toolbox [12]. The baseline was removed from the EEG signal and low-pass filtering at a cut-off frequency of 45 Hz was performed using a linear-phase FIR filter. EEG signals were then high-pass filtered at a cut-off frequency of 0.1 Hz and notch filtered at 50 and 60 Hz using a linear phase FIR filter. The order of the filter in all cases was 300. After filtering the data, Independent Component Analysis (ICA) decomposition was performed to detect and remove artifacts such as eye blinking and muscle movements. A minimum of 5-8 channels is required to perform ICA [34]. Once the data was clean enough, we extracted two-second epoch averaged data from resting, drawing and manipulation tasks by performing back-to-back epoching with a 0.5-sec difference between epochs. The users 1, 2, 4 and 10 were competent users in AutoCAD.

3.5. Functional Brain Network

The pre-processed EEG signals were used in the construction of NTE connectivity matrices, where each cell denotes the NTE value from one electrode to another. The normalization was done by subtracting a noise matrix (averaged shuffled TE matrix) from the Transfer Entropy (TE) matrix. The NTE matrices were used to create both binary and weighted directed FBN. To analyze the results, we used the graph analysis measure such as the Connectivity density, clustering coefficient, and node strength.

4. Results and Discussion

As all the participants were new to the use of MMIS. The order of the tasks were not randomized since there was no advantage of changing effect observed in the second task (gesture state). There was no significant correlation found between competency levels and task completion time. One-way ANOVA and t-test were used to demonstrate the differences between various EEG indices such as clustering coefficient, mean information flow, etc.

4.1. Analysis of directed binary FBNs

The section shows the results of the analysis performed on binary directed FBNs constructed using the connectivity matrix calculated by NTE. The Fig 2 showed the NTE connectivity matrices for two users during various states. As shown in Fig. 2, the brain connectivity increased progressively as the cognitive activity increased from rest state to keyboard and gesture drawing states. Fig. 3 shows the connectivity density for all 12 users. The connectivity density is higher in keyboard and gesture drawing states than the baseline resting state, inferring more connections between electrodes to accommodate more active information flow. This means that the brain recruits a higher number of neurons to facilitate high cognitive activity processes in keyboard and gesture drawing states.

If we compare the keyboard and gesture connectivity density, an increase in connectivity

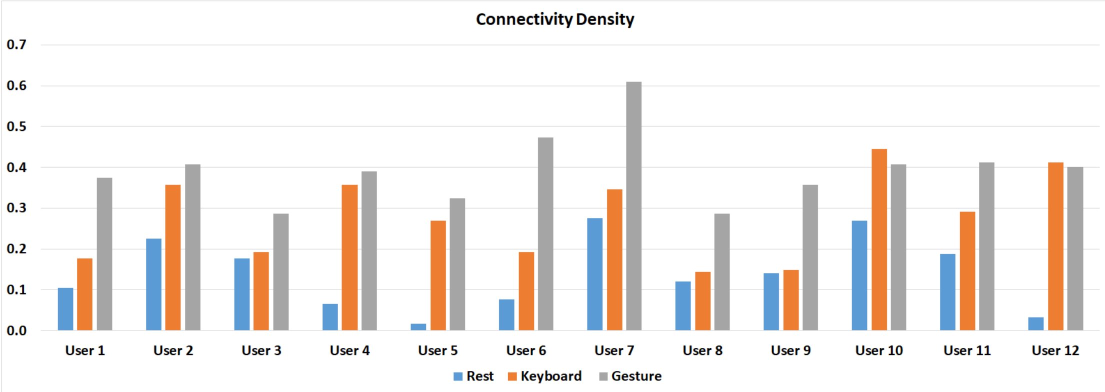


Figure 3. Comparison of connected density for all users during rest, keyboard and gesture drawing states

density was seen except for user 10 (competent user) and 12. The increase in connectivity density in gesture drawing state from the keyboard drawing state is probably due to the execution of a number of simultaneous processes (motor cognition, visual processing, designing). Fig.

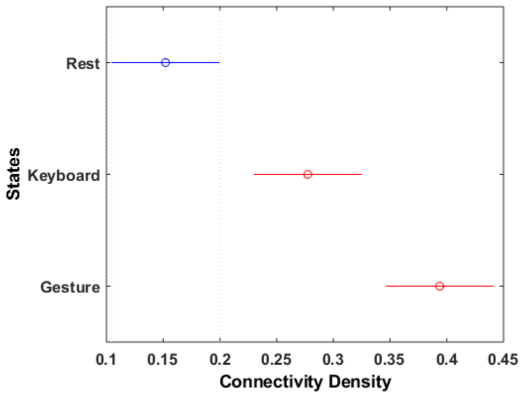


Figure 4. Multiple comparison test of connectivity density group mean for 12 users during rest, keyboard and gesture drawing states

4 shows the statistical significance of the connectivity density of all the users during the three states. The lines extended out from the mean shows the confidence intervals which means that the group means are significantly different because there was no overlap. The clustering coefficient was calculated from the binary directed FBNs across the electrodes for all participants and the results of two participants (User 6 and 12) have been shown in Fig. 5. It can be seen that the clustering coefficient value increases for almost all the electrodes during the cognitive activity compared to the rest state. This shows that each electrode is communicating effectively with its neighboring electrodes to form clusters which represent an increase in local efficiency of the information transfer between electrodes. The clustering coefficient values also showed that the electrodes from right side frontal lobe and left side occipital and parietal lobes are communicating more with the nearest neighbors. Table 1 shows the statistical significances of the differences between means of clustering coefficient across electrodes during keyboard and gesture drawing states for all participants computed using two-tailed t-test at $\alpha = 0.05$. The highlighted entries in the tables represent the competent users of AutoCAD. The results show that the mean difference is significantly different in keyboard and gesture drawing states for almost all the users except for user 1, 2, and 4 (competent users) represented in blue in Table 1. The mean difference is significant for all the users in rest and keyboard and rest and gesture drawing states.

We have also calculated the degree centrality for all participants from the NTE matrix. Degree centrality shows the importance of a node in the network. Fig. 6 shows the topographic

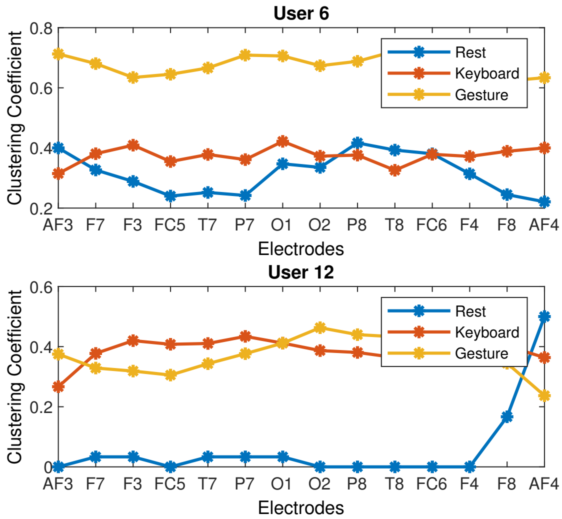


Figure 5. Clustering coefficient across electrodes for during rest, keyboard and gesture drawing states of two users

Table 1. Statistical validation of clustering coefficient values for all user during keyboard and gesture drawing states

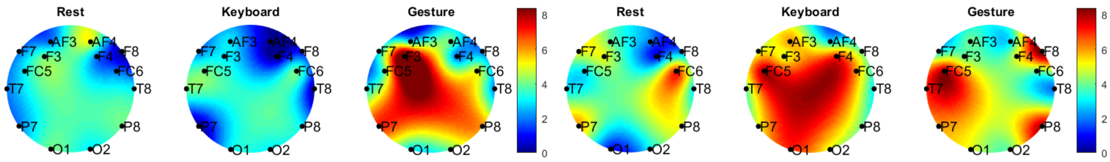
Users	Mean Diff.	95% CI		P
User 1	0.0744	-0.0110	0.1597	0.0824
User 2	-0.0180	-0.0609	0.0250	0.3828
User 3	0.0655	0.0396	0.0913	0.0001
User 4	0.0173	-0.0425	0.0771	0.5421
User 5	0.1728	0.0575	0.2881	0.0065
User 6	0.0189	-0.0364	0.0741	0.0474
User 7	0.1855	0.1280	0.2431	0.0000
User 8	0.1403	0.0591	0.2214	0.0025
User 9	0.3033	0.2722	0.3344	0.0000
User 10	0.1395	0.1036	0.1753	0.0000
User 11	0.2020	0.1652	0.2388	0.0000
User 12	-0.0512	-0.1061	0.0037	0.050

map of degree centrality data of 2 samples including novice and competent users in 2D circular view of all brain states. The topographical map was customized such that the color map scales from minimum degree centrality value to maximum degree centrality value to visualize subtle changes. The blue color represents the minimum value and the red represents the maximum value of degree centrality. The user in the drawing state shows greater engagement than the resting state. The major focus is seen in the frontal area of the brain. Both drawing with keyboard/mouse and speech/gesture requires intense visual attention which shows elicited central and frontal areas in the brain. Some competent users of AutoCAD show a small variation in degree centrality across electrodes in keyboard and gesture drawing state compared to other users. Table 2 shows the results of t-test at $\alpha = 0.05$ (two-tailed) between means of average degree

Table 2. Statistical validation of mean degree centrality across electrodes for all participants during rest, keyboard, and gesture drawing states

States		Mean Diff.	95% CI		P
Keyboard	Rest	1.5000	0.4778	2.5222	0.0080
Gesture	Rest	2.9762	1.9589	3.9935	0.0000
Gesture	Keyboard	1.4762	0.5625	2.3899	0.0045

centrality across electrodes in all three states for all users and the results show that the mean difference is significantly different across all cognitive states. The maximum mean difference



(a) User 9 (Novice) **(b)** User 10 (competent user user)

Figure 6. Sample degree centrality topographical plot of two uses during rest, keyboard and gesture drawing states

was observed in gesture drawing and rest states.

Table 3. Electrodes with maximum variance in keyboard and gesture drawing states using LDA

Graph Measure	**Electrodes**				
Clustering coefficient	AF4	O2	P8	T8	FC6
Degree Centrality	F7	FC5	T7	O2	P8

Linear Discriminant Analysis (LDA) was used to find the electrodes that showed the maximum variance between keyboard and gesture drawing task. The results shown in Table 3 state that for the clustering coefficient the maximum variation has been seen in the electrodes that are on the right side of the hemisphere compared to the left hemisphere electrodes. It can also be interpreted as the electrodes on right-hemisphere form clusters more often than the left hemisphere electrodes. In the case of degree centrality, the maximum difference was seen in the frontal left hemisphere (F7, FC5, T7) and back right hemisphere (O2, P8). This indicates that the receiving and transmitting of information are from these electrodes more than the other electrodes.

4.2. Analysis of directed weighted FBNs

We have used the weighted FBNs to find the mean information flow and node strength for all the users. Fig. 7 shows the multiple comparison test of the average node strength of all the users

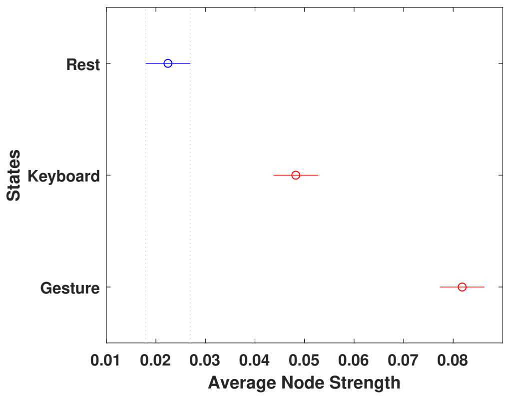


Figure 7. Multiple comparison test of node strength group mean for 12 users during rest, keyboard and gesture drawing states

across all electrodes in three states. The results clearly show that the node strength in gesture drawing state is more than the keyboard drawing and rest state and the results are statistically significant as seen in Fig. 7. The electrodes in the frontal lobes send and receive more information while drawing with gestures compared to the keyboard state. The total information flow from each electrode to all the other electrodes has been calculated by the row-wise summation of the NTE connectivity matrix. Fig. 8 shows one-way analysis of variance (ANOVA) results

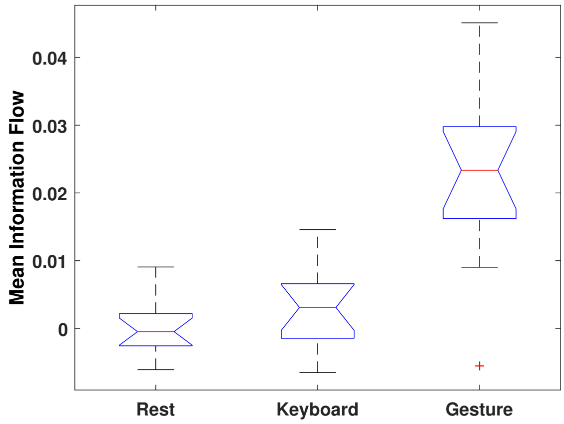


Figure 8. Multiple comparison test of node strength group mean for 12 users during rest, keyboard and gesture drawing states

on the mean information flow across electrodes for all participants. The mean information flow increased from approximately 0.005 to 0.02 when the user was using multi-modal inputs instead of keyboard and mouse for drawing. Table 4 shows the statistical significance of the differences

Table 4. Statistical validation of total information flow for all users during rest, keyboard and gesture drawing states. (MD = mean difference, CI = confidence interval

Users	Keyboard-Rest			Gesture-Rest			Gesture-Keyboard		
	MD	95% CI		MD	95% CI		MD	95% CI	
User 1	0.0217	0.0092	0.0341	0.0674	0.0471	0.0877	0.0457	0.0174	0.0740
User 2	**0.0076**	-0.0019	0.0170	0.0149	0.0017	0.0281	**0.0073**	-0.0060	0.0206
User 3	**0.0059**	-0.0015	0.0133	0.0255	0.0154	0.0356	0.0196	0.0065	0.0327
User 4	0.0402	0.0328	0.0476	0.0369	0.0279	0.0459	**-0.0033**	-0.0118	0.0053
User 5	0.0379	0.0143	0.0615	0.0387	0.0157	0.0618	**0.0009**	-0.0276	0.0293
User 6	0.0153	0.0012	0.0294	0.0570	0.0374	0.0767	0.0417	0.0259	0.0576
User 7	0.0130	0.0025	0.0235	0.1064	0.0738	0.1389	0.0933	0.0618	0.1249
User 8	0.0139	-0.0019	0.0297	0.0370	0.0170	0.0571	0.0231	-0.0015	0.0477
User 9	**-0.0005**	-0.0148	0.0139	0.0397	0.0245	0.0549	0.0402	0.0207	0.0596
User 10	0.0385	0.0195	0.0575	0.0632	0.0345	0.0920	**0.0248**	-0.0118	0.0613
User 11	0.0447	0.0360	0.0534	0.0738	0.0555	0.0920	0.0291	0.0089	0.0492
User 12	0.0693	0.0527	0.0860	0.1425	0.1170	0.1680	0.0731	0.0474	0.0989

in means of total information flow for all users using t-test with $\alpha = 0.05$ (two-tailed). The bold values of mean difference showed that the difference was not statistically significant i.e. $p > 0.05$. In case of gesture and keyboard drawing analysis, the users 2, 4, 10 (competent users) and 5's mean information flow difference was not significant. The possible reason can be that the user 2, 4 and 10 have some previous knowledge of AutoCAD but this can't be generalized as other users did not show the same trend. We also applied LDA to information flow and node strength values to find out the electrodes that provide maximum variance during keyboard and gesture drawing states and the results are shown in Table 5. In the case of node strength, the electrodes in the frontal lobes were sending and receiving more information than other electrodes. The electrodes in the frontal right hemisphere of the brains (F4, F8, AF4) have shown more variation in node strength compared to other electrodes. The frontal and parietal lobes electrodes mean information flow variations are more than the other regions when using gesture drawing states. We have also tried to find the correlations between the participants experiment completion time and mean information flow patterns using LDA and found that the information flow from right hemisphere was more compared to left-hemisphere specifically in the frontal and central cortex for participants who completed the experiment within 3 minutes.

Table 5. Node strength and mean information flow electrodes with maximum variance in keyboard and gesture drawing states

Graph Measure	**Electrodes**				
Node strength	FC5	T7	F4	F8	AF4
Mean Information Flow	FC5	P7	P8	FC6	F8

The results show that the cognitive activity of the users increased in the gesture drawing state. The increase in the activity could be related to other underlying perceptual and motor functions and it could possibly imply the differences in motor processes between two tasks. The significant differences in the frontal cortex activities also point toward the increase in the motor activities in the second task. However, the increase was less for some competent (user 2, 4, 10) and novice (user 5) users. This may indicate that with a little training the users will be able to demonstrate the same cognitive activity level as they show in keyboard drawing state. The novice's efficiency can be increased if we can simulate frontal and central lobes of the brain more often than the other lobes. One way to achieve this is to ask the users to use their short-term memory by displaying some hints or other related information for the experiment.

5. Conclusion

In this paper, NTE has been applied to construct functional brain networks from EEG signals to study the user's cognitive activity in rest, traditional input (keyboard and mouse) and multi-modal input (speech and gesture). After pre-processing of the EEG signal, we have extracted averaged 2 seconds epochs to construct the connectivity matrix using normalized transfer entropy. The averaging of epochs was done to remove the noise from the signals and to extract more global properties of the drawing phenomena. Functional brain networks were constructed using the NTE matrix. Graph theory-based measures were used to analyze the FBNs. Both binary and weighted FBNs were used to study different cognitive states. The results show that the cognitive activity of the user increased when they were using multi-modal input for drawing 3D objects in AutoCAD. The connectivity density, clustering coefficient, and degree centrality results demonstrate that the information transfer between electrodes increased in gesture drawing state from keyboard drawing state. The mean information flow and node strength showed that the maximum variation in sending and receiving information was seen in frontal and central lobes because drawing with multi-modal input requires intense attention and motor cognition. 3 out of 4 competent user users showed that the variation in cognitive activity was less when they moved from keyboard to gesture drawing state.

The limitation of this work includes no counterbalancing of the experimental conditions, small number of users, unbalance dataset, and low number of EEG electrodes. In future work, we will expand this analysis to study the information flow within the hemispheres and various brain regions characteristics. The future analysis will also focus on finding the source and sink brain regions of information flow and how to detect user competency to design adaptive CAD systems.

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