Towards a Cognitive Metric using Normalized Transfer Entropy

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Abstract

Investigation of functional brain networks using various complex network and inferential statistical techniques in various studies have provided insight into the intricacies of the patterns of structural and functional connectivity of human brain in recent years. Most of these studies have analysed the brain networks as being undirected where the direction of information flow between various brain regions has not been considered. The directions of information flow in the functional brain networks provide additional information on how one brain region influences the other and identify influential brain regions serving as network hubs during information processing. This study used information-theoretic concept of normalized transfer entropy on the EEG data to construct directed functional brain networks during five different brain states. Using a mix of signal processing, information and graph-theoretic techniques, the findings demonstrated that directed functional brain networks constructed using normalized transfer entropy is very sensitive to the changes in the cognitive tasks and this sensitivity can be used to develop a quantitative metric to measure cognition.

Keywords: Cognitive load; Cognitive metrics; Normalized transfer entropy; Directed functional brain network; EEG; Graph theory; Complex network metrics.

1. Introduction

The human brain is a complex network resulting from dynamic interactions among billions of neuronal elements. When such interactions are based on physical or anatomical connections between neuronal elements such as synapses and axonal projections, it is known as a structural brain network. Functional brain networks (FBN), alternately, are derived from time series observations of brain function using various neuroimaging techniques such as electroencephalography (EEG) and magnetoencephalography (MEG) [1, 2]. Of the two, EEG is the most cost-effective and easily accessible, providing a powerful non-invasive tool from which functional brain networks can be constructed by recording neural activity at scalp level through multiple electrodes.

Recent advancements in the quantitative analysis of EEG signals have proven more sensitive than visual inspection; as a result, functional coupling and correlational measures between brain regions have enabled a better understanding of the neural substrates of cognitive function [1, 3]. There appears, however, to be very few studies exploring directed FBNs constructed using asymmetrical measure of effective connectivity or causal interaction, such as Granger causality or transfer entropy [1]. This is perhaps, surprising given that directed networks exhibit more prominent features than an undirected network by providing the direction of information exchange between the regions or nodes.

Although Granger causality is often used to identify causal relationship in EEG data, it is limited to a linear model of interaction [4] and, as a result, fails to identify accurate causal relationships in systems composed of highly nonlinear units such as the human brain. Although some attempts have been undertaken to extend Granger causality to include nonlinear signal features, it is necessary for the models selected for implementing the measure be specifically matched to the dynamic characteristics of the signals [5].

In comparison, the information-theoretic measure of transfer entropy (TE) determines both the direction of the information transfer between two processes as well as quantifies that information transfer [6]. TE estimates the amount of activity of a system which is not dependent on its own past activity but on the past activity of another system. It does not require a model of the interaction and is inherently non-linear [4]. As a consequence, TE has been used in various applications such as identifying causal relationships between pairs of genes [7], investigating the influence of heart rate to breath rate and vice versa [6], information transfer between auditory cortical neurons using spike train data [8], exploring effective connection on MEG data associated with different types of task [4, 9], and for the localization of epileptic foci using EEG data [10, 11]. TE has not, however, been applied to more generalised cognitive processing; specifically, the degree of overall cognitive load that an individual experiences while performing a particular cognitive task. Given that TE is both robust enough and sensitive enough to capture minor variations in brain data; it appears an ideal metric for capturing subtle variations in overall cognitive processing. To thus test the suitability of TE as an analytical tool for investigating cognitive load variations, EEG data was collected during five different cognitive tasks of increasingly higher degrees of cognitive load. The FBNs constructed using the Normalized Transfer Entropy (NTE) has been exhibited high sensitivity to varying cognitive loads. This sensitivity exploited to demonstrate the efficacy of NTE in detecting and quantifying cognitive load induced changes in FBN. Section 2 will also discuss the current literature on quantifying cognitive load while sections 3 and 4 will describe NTE and the complex network metrics used in the current study. The methodology and discussion on results will be presented in sections 5 and 6 respectively, while section 7 provides a brief conclusion and likely future direction for this research.
2. Quantifying Cognitive Load

Cognitive load or workload in general can be defined as the portion of an individual’s processing capacity actually required to perform a particular task [12]. Minimising, or at least managing, the degree of cognitive load is a primary research goal for a variety of disciplines, ranging from cognitive psychology to human factors; however, cognitive load indices can be categorized into just three major classes - subjective, physiological and task/performance-based [13, 14]. The first of these, subjective, is based on the assumption that people can accurately perceive and interpret the amount of cognitive effort they expend on a particular situation or to perform a particular task, which may or may not be a reasonable estimate [15]. Subjective measurements can only provide static cognitive load, because they are typically administered after the task is completed [16].

Task/performance based methods are, alternately, a type of dual-task technique that involve the performance of both a primary and a secondary task [17]. Measurement can be of either the primary task (learner performance of the task of interest), or the secondary task (performance when a second task is performed concurrently with the primary task) [15]. In this method, the individual performs two or more tasks simultaneously. Based on the assumption that performance is related to workload, a higher workload should result in a performance breakdown [14]. As a consequence, when the primary task requires higher mental resources, the performance on the secondary task decreases. Error rates, accuracy, reaction or response times to the secondary tasks, and the ratio of the actual completion time to an ideal completion time are used to measure the performance in such environments [14, 17]. The limitation of these techniques is the introduction of an unnecessary secondary task purely to measure the workload of a primary task.

Finally, physiological techniques are based on the assumption that changes in cognitive functioning are reflected in changes in physiological measures [15], which, in turn, are a direct and objective measure of cognitive load [18]. Physiological measurement can be categorized into two main types: psychophysiological and neuroimaging [19]. Psychophysiological measurements are reliable, well-validated [20] techniques that capture indicators that are closely related to nervous system function although they do not measure brain activity directly. Psychophysiological tools include eye tracking, skin conductance response/Galvanic skin response, electrocardiogram/heart rate variability and facial electromyography (fEMG) [19, 21, 22]. Although the use of these tools are relatively easy and cheap, all pose problems of interpretation as different cognitive challenges can result in similar psychophysiological responses [20]. It is therefore impossible to pinpoint a specific process underlying a response [19].

Brain imaging, alternately, is currently the most popular neuro scientific approach for measuring cognitive load [20], due in no small part to its ability to capture direct indicators of neural activity. Currently, the most popular neuroimaging tools used are functional magnetic resonance imaging, positron emission tomography, functional near infrared spectroscopy, electroencephalography, and magnetoencephalography [19, 21]. Previous studies using such tools to investigate cognitive load have, however, been limited to distinguishing between only two cognitive load states – low versus high and load versus overload [23, 24]. Thus far, investigations focussing on quantitative metrics of degrees of cognitive load have been scarce; the purpose of the current paper is to identify EEG responses to varying degrees of load through the application of NTE.

3. Normalized Transfer Entropy

Assuming that the two time series of interest \( X = x_t \) and \( Y = y_t \) can be approximated by Markov process, Schreiber proposed a measure of causality called Transfer Entropy to compute the deviation from the following generalized Markov condition as shown in equation 1 [6],

\[
p(y_{t+1} | y_t^n, x_t^m) = p(y_{t+1})
\]

where \( x_t^m = (x_{t}, \ldots, x_{t-m+1}) \), \( y_t^n = (y_{t}, \ldots, y_{t-n+1}) \), while the subscript \( t \) denotes the considered state (or time step); \( m \) and \( n \) represent the orders (memory) of the Markov processes \( X \) and \( Y \) respectively; and \( p(\cdot) \) represent the transitional probability. Schreiber represented transfer entropy from \( X \) to \( Y \) as shown in equation 2 [25],

\[
TE_{X \rightarrow Y} = \sum_{y_t+1, y_t^n, x_t^m} p(y_{t+1}, y_t^n, x_t^m) \log \left( \frac{p(y_{t+1} | y_t^n, x_t^m)}{p(y_{t+1} | y_t^n)} \right)
\]

\( TE_{X \rightarrow Y} \) can be regarded as the information about future observations \( y_{t+1} \) gained from the past observations of \( y_t^n \) and \( x_t^m \) minus the information about future observations \( y_{t+1} \) gained from past observations of \( y_t^n \) only. The TE measure is inherently asymmetric and based on transition probabilities, so it incorporates directional and dynamic information. TE can be in the range \( 0 \leq TE_{X \rightarrow Y} < \infty \).

In the current study, for the computation of TE, two additional steps were included to improve the calculation accuracy [8, 26]. Due to the finite size and non-stationarity of EEG data, TE matrices usually contain large amounts of noise. Noise/bias has been removed from the estimate of TE by subtracting the average transfer entropy from \( X \) to \( Y \) using shuffled version of \( X \) denoted by \( < TE_{X \rightarrow Y, shuf} > \), over several shuffles [26]. \( X_{shuf} \) contains the same symbol as in \( X \) but those symbols are rearranged in a randomly shuffled order. Then, normalized transfer entropy is calculated from \( X \) to \( Y \) with respect to the total information in sequence \( Y \) itself. This will represent the relative amount of information transferred by \( X \). The normalized transfer entropy (NTE) is shown in equation 3 as follows [8]:

\[
NTE = \frac{TE_{X \rightarrow Y}}{TE_{Y \rightarrow X}}
\]
In equation 3, \(H(y_{t+1}|y_t)\) represents the conditional entropy of \(Y\) at time \(t+1\) given its value at time \(t\) as shown in equation 4.

\[
H(y_{t+1}|y_t) = - \sum_{y_{t+1}, y_t} p(y_{t+1}, y_t) \log \frac{p(y_{t+1}, y_t)}{p(y_t)}
\]  

(4)

NTE is in the range \(0 \leq NTE_{X\rightarrow Y} \leq 1\). NTE is 0 when \(X\) transfers no information to \(Y\), and is 1 when \(X\) transfers maximal information to \(Y\).

4. Directed Functional Brain Network Analysis

According to Graph Theory, a graph is a mathematical model that consists of vertices (nodes) where the connection between each pair of vertices is called an edge (link) [1, 2]. In the case of FBNs, scalp electrodes are considered as vertices which represent the activity of underlying neuronal populations and the connections/links between these electrodes are measured using a correlation representing the weight of the edge. Complex network metrics are quantitative analysis techniques that can be used to characterize the connectivity pattern of brain networks in different cognitive states. A broad range of complex network metrics can be used to characterize brain networks, such as connectivity density, characteristic path length, clustering coefficient and different types of centrality measures. A brief description of the complex network metrics used in this study is presented in the following subsection.

4.1 Connectivity Density

Connectivity density is the actual number of edges in the graph as a proportion of the total number of possible edges [1]. It is also referred to as physical cost or wiring cost or connectivity cost. For a directed graph with \(n\) nodes where there are no self-connections/loops, the total number of possible connections is \(n^* (n-1)\).

4.2 Clustering Coefficient

Clustering coefficient for directed network has been developed by Fagiolo [27]. In a directed graph, 3 nodes can generate up to 8 triangles (closed group). The clustering coefficient for node \(i\) represents the ratio between all directed triangles actually formed by \(i\) and the number of all possible triangles that \(i\) could form. The clustering coefficient measures the cliquishness of a network and represents how well the neighbourhood of a node is connected. If it is fully connected, the clustering coefficient is 1, whereas a value close to 0 implies that there are hardly any connections. High clustering coefficient is related to the high local efficiency of information transfers [1]. It is mostly used to measure the functional segregation.

4.3 Characteristic Path Length

The average shortest path length between all pairs of nodes in the network is known as the characteristic path length. The shortest path between node \(i\) and node \(j\), \(d(i, j)\) can be defined as the minimum number of nodes that it has to traverse to reach node \(j\) from node \(i\). Shortest path length, between nodes \(i\) and \(j\) is given by,

\[
d_{ij} = \sum_{a_{uv} | gi \to j} a_{uv}
\]

where, \(gi \leftrightarrow j\) is the shortest path between \(i\) and \(j\). So, the characteristic path length of the network [28] is given by,

\[
L = \frac{1}{n} \sum_{i \in N} L_i = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \neq i} d_{ij}}{n-1}
\]

where, \(L_i\) is the average distance between node \(i\) and all other nodes. It is used mostly for measuring the functional integration. The shortest path length indicates the high global efficiency of parallel information transfer [1]. It is used for measuring the functional integration.

5. Methods

5.1 Participants

Eight healthy, right-handed adults (six males and two females) volunteered to participate in the EEG data collection during cognitive load experiments (age range 28-65). The experiments were conducted at the Cognitive Neuroengineering Laboratory of the University of South Australia. The participants were recruited from the academic and professional staff and student populations of the University of South Australia (Mawson Lakes campus), as well as the wider Adelaide general community. All participants reported normal hearing, normal or corrected-to-normal vision without any history of psychological, neurological or psychiatric disorders. Before the experiment started, the experimental procedures had been explained to all participants and thus signed, informed consent were obtained.

5.2 EEG Data Acquisitions

EEG data were acquired at a sampling rate of 1000 Hz through a 40 channel Compumedics Neuroscan Nuamps amplifier using Curry 7 software [29, 30]. Prior to data collection, each participant was fitted with an appropriate sized 32 channel Quikcap. The 30 electrode sites used in the current study were based on the international 10-20 convention: FP1, FP2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T3, C3, Cz, C4, T4, TP7, CP3, CPz, CP4, TP8, T5, P3, Pz, P4, T6, O1, Oz and O2 with the average of two earlobes (A1, A2) used as the reference. Continuous EEG data were collected during five different brain states: eyes open (baseline) plus mild, moderate, heavy and extreme cognitive load conditions. Impedance values of all electrodes were checked using Curry with no recording undertaken until all channel impedances were below 50 kΩ. All stimulus onsets and participant responses were time-marked on the EEG.
record using Compumedics Neuroscan STIM 2 software [31]. The experimental setup for EEG data acquisition during cognitive load experiments has been shown in Figure 1. A brief description of the stimulus used in this experiment is presented in the following subsection.

![Figure 1. EEG data acquisition paradigm](image)

5.2.1 Baseline - Eyes Open (EOP) and Eyes Closed (EC)

To obtain baseline brain activity, participants were asked to firstly stare at a blue fixation star on the STIM computer monitor for 2 minutes. They were then asked to close their eyes and sit calmly for further two minutes. In this study, we only used EOP data for analysis and comparison with the cognitive load states.

5.2.2 Mild Cognitive Load (MiCL) 1-back Stroop Task

To evoke cognitive activity, the participant was instructed to undertake a 1-back Stroop task. The standard Stroop task is one of interference. Known to evoke large effect sizes and validated as being statistically reliable, the task requires participants to respond to a series of visually displayed congruent and incongruent word stimuli. A congruent stimulus, for example, would be the word red typed in red coloured font; an incongruent stimulus would be the word red typed in yellow coloured font. A 1-back variation on the standard Stroop task involves inserting some type of neutral stimulus between the presentation of the target stimulus and the cue to respond. In the current study, a fixation cross (neutral) was inserted between the stimulus presentation (Stroop stimulus) and the cue to respond via the keyboard button press “Y” if the font colour and word meaning were the same or “N” if they were different. This 1-back component was used to add a second layer of higher cognitive processing (working memory) to the base level of the Stroop task itself (attention).

5.2.3 Moderate Cognitive Load (MoCL) 1-back Stroop Task with Go/No-go Variation

Go/No-Go (G/NG) tasks are a type of recognition reaction time (RT) task whereby participants must respond to some stimuli (Go) whilst inhibiting their response to other stimuli (no-go). In the current study, participants were required to again undertake a 1-back Stroop task but with the explicit instruction to ignore any stimulus words appearing in blue font whether that stimulus was congruent (the word blue in blue coloured font) or incongruent (the word red in blue coloured font). This thus placed an additional layer of load on both working memory and attention processes.

5.2.4 Heavy Cognitive Load (HCL) - Moderate Cognitive Load with Auditory Distraction

To further tax global cognitive processing, bottom-up processing was then increased through the addition of auditory distraction. Participants again performed the 1-back Stroop Task with Go/No-go Variation whilst also listening to a pre-recorded sound-track constructed using dichotic listening principles; that is, different sounds played to different ears at the same time (e.g. bird song on left channel, tornado siren on right channel). They were also instructed to listen for a specific stimulus (a spoken number) as part of that sound-track and further told that they would be asked a question about that stimulus at the completion of the task. This thus provided personal salience, as well as encouraging attention to the task. To ensure heightened auditory monitoring throughout the task, no number was actually spoken on the soundtrack.

5.2.5 Extreme Cognitive Load (ECL) – Moderate Cognitive Load with Auditory and Visual Distraction

In the final task, participants were again asked to perform the 1-back Stroop Task with Go/No-go Variation whilst also listening to a pre-recorded sound-track. Additionally, equal numbers of neutral and aversive distractor images were inserted between and with-in each visual stimulus. As per the auditory-only distraction, participants were also asked to attend to a specific stimulus type (e.g. tool) and advised that a question would be asked at the conclusion of the task; thus, participants were asked to attend to one specific distractor per modality.

5.3 EEG Signal Pre-processing

From the collected EEG recordings of eight participants, two were excluded based on excessive residual artefacts such as channel saturation during recording or muscle movements. Pre-processing of the remaining six participant’s EEG data was done by applying band pass filter of 1-70 Hz and a notch filter at 50 Hz. To detect eye blinks one of the typical eye blinks was selected by visual inspection and the remaining eye blinks detected using Curry 7 template matching. These eye blink artefacts were then removed using principal component analysis (PCA). Bad blocks were removed manually. In each of the cognitive load states, excessively fast and slow responses were excluded. As a result, only those trial epochs
with RTs between 1.5 and 3.5 seconds were used in this study. In each cognitive load state, selected epochs were then extracted from the stimulus onsets, and averaged. For the comparison of each cognitive load state with baseline (EOP), 50 chunks of EEG data of two seconds duration were randomly selected from the EOP data, and then averaged.

5.4 Analysis Framework
The pre-processed EEG data during EOP, MiCL, MoCL, HCL and ECL were then used for the computation of TE matrices, where each cell of the TE matrices represents the TE value from one electrode to another. For noise removal, an average shuffled TE matrix (noise matrix) was calculated and subtracted from the original matrix. The constructed NTE matrices were then binarized for the analysis using different types of complex network metrics. The data, information processing and associated computational steps are illustrated in Figure 2.

6. Results and Discussion
For all participants, the connectivity density of the constructed binary directed FBN during different brain states (EOP, MiCL, MoCL, HCL and ECL) has been calculated and shown in Figure 3. Here, EOP has the least connectivity density and ECL has the highest connectivity density. An increasing pattern of connectivity density across the states for all the participants was observed due to the increasing amount of cognitive load. The results demonstrated that the connectivity density of the directed FBN increases with increase in induced cognitive load. Thus, the connectivity density is directly proportional to the amount of cognitive load applied.
The characteristic path length of the FBN during different brain states has been calculated for all the participants and displayed in Figure 4. Due to the increase in connectivity density, a decreasing pattern of characteristic path length across the states is noticed for all the participants with increasing amount of cognitive load. From the results, we can infer that the induced cognitive load increases the connectivity density which in turn reduces the characteristic path length of directed FBN to facilitate more active information flow.

For all the participants, clustering coefficient value of each electrode during different brain states (EOP, MiCL, MoCL, HCL and ECL) has been calculated. Due to the space limitation, the clustering coefficient results for only one participant has been shown in Figure 5. Clustering coefficient value increases in almost all of the electrodes during cognitive load when compared to the baseline state (EOP). The increasing clustering coefficient demonstrated that the information transfer among the neighbouring nodes of each electrode increases with increasing cognitive load.

The clustering coefficient values of all the electrodes plotted on the 3D head surface in different brain states using Headplot function has been shown in Figure 6. To visualize the minor changes of clustering coefficient value in different brain states, the colour map scale of Headplot function has been customized. We have used the colour map scale from minimum clustering coefficient value to maximum clustering coefficient value among the clustering coefficient value of all the electrodes of all the brain states [3, 32]. Blue colour represents the minimum clustering coefficient value and the red colour represents the maximum clustering coefficient value. The increased clustering coefficient during increased cognitive load has been demonstrated by the appearance of brighter colour around the electrodes on the head scalp.

To find the statistical significance of mean clustering coefficient difference during different brain states, one way analysis of variance (ANOVA) and Tukey HSD test at $\alpha = 0.05$ have been applied. Due to the page limitation, the multi-comparison result for four participants has been shown in Figure 7. For four participants, the pairwise comparison results of mean difference and confidence interval have been shown in Table 1. The mean clustering coefficient value is significantly different during different brain states in almost all of the participants.
Figure 6. Visualization of clustering coefficient value on head surface in different brain states using Headplot function

Table 1. Statistical validation of mean clustering coefficient difference during different brain states

<table>
<thead>
<tr>
<th>States</th>
<th>Subjects</th>
<th>Mean Difference</th>
<th>Confidence Interval</th>
<th>Subjects</th>
<th>Mean Difference</th>
<th>Confidence Interval</th>
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<td>-0.0652*</td>
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<td>P2</td>
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<td></td>
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<tr>
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*Mean difference is significant at p < .05 level.
7. Conclusion

The results demonstrate that directed functional brain networks constructed using normalized transfer entropy are highly sensitive to changes in neural activity directly related to changes in degrees of cognitive load. Given this sensitivity, it strongly suggests that the NTE approach can be used to develop objective, quantitative metrics to measure cognition. Such a cognitive metric has potential application in the diagnoses of cognitive impairments. Other practical applications of this research could be the development of simple devices for measuring cognitive load in real time. Such a device could then be used in adaptive intelligent systems as well as in many safety critical systems which require intensive mental activity such as driving, air/train traffic control system, flying an aeroplane etc. Future work will concentrate on developing a generic cognitive metric or cognitive barometer that could be used by a variety of participants and situations to measure cognitive load.

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References


[29] CURRY 7 EEG Acquisition and Analysis Software. Compumedics Neuroscan USA Ltd


[31] STIM 2 Stimulus Delivery and Experiment Control Solution. Compumedics Neuroscan USA Ltd