Cognitive Activity during Web Search

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ABSTRACT
Searching on the Web or Net-surfing is a part of everyday life for many people, but little is known about the brain activity during Web searching. Such knowledge is essential for better understanding of the cognitive demands imposed by the search system and search tasks. The current study contributes to this understanding by constructing brain networks from EEG data using normalized transfer entropy (NTE) during three Web search task stages: query formulation, viewing of a search result list and reading each individual content page. This study further contributes to the connectivity analysis of the constructed brain networks, since it is an advanced quantitative technique which enables the exploration of brain function by distinct and varied brain areas. By using this approach, we identified that the cognitive activities during the three stages of Web searching are different, with various brain areas becoming more active during the three Web search task stages. Of note, query formulation generated higher interaction between cortical regions than viewing a result list or reading a content page. These findings will have implications for the improvement of Web search engines and search interfaces.

Categories and Subject Descriptors
H.3.3 [**Information Search and Retrieval**]: Search process

General Terms
Measurement, Design, Experimentation

Keywords
Information seeking; cognitive load; interactive information retrieval (IIR); EEG; normalized transfer entropy; graph theoretical analysis

1. INTRODUCTION
Interactive information retrieval is cognitive in nature [1, 2]. To understand the search process, it is necessary to understand individual users' cognitive activity or load during information interaction [3]. Previous research by Kim and Rieh [4], used the dual-task method for assessing mental effort during Web searching, finding significant differences in user mental effort between viewing search results and reading contents pages. Similarly, Gwizdka [5] used dual-task method to demonstrate dynamic changes in cognitive load in the task stage level of Web searching, reporting significantly higher average cognitive load during query formulation. Cole, Gwizdka, Lui and Belkin [6] further measured dynamic cognitive load during Web searching using eye movement patterns. They found that cognitive effort increases as the task difficulty increases. The dual-task method which is based on users' performance and reaction time to a secondary task, does not, however, directly measures brain activity. Similarly, eye tracking does not measure brain activity effectively; it is assumed that the captured indicators are closely related to the nervous system. As previous studies have relied on these inferential methods, how brain regions connect during effective Web searching, and which region acts as an information convergence region or hub remain unknown. Neuroimaging techniques such as EEG can, however, provide more direct measures of users' cognitive activity and recent studies have also highlighted the potential of neuroscience to contribute in interactive information retrieval [7]. The current study aims to capture the dynamic interactions between neuronal elements of the human brain during Web search task stages by constructing functional brain networks (FBNs) from time series observations of EEG signals using NTE [8]. We selected EEG for measuring cognitive load during Web search interactions because it is an inexpensive and non-invasive technology with high temporal resolution, and allows easy setup of a Web search experiment in a user-friendly environment. The rest of the paper is structured as follows: Section 2 will discuss the current literature on NTE; Section 3 will describe the methodology. The discussion of results will be presented in Sections 4, followed by a brief conclusion and future research directions in Section 5.

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2. NORMALIZED TRANSFER ENTROPY
Transfer Entropy (TE) is an information theoretical measure which determines the direction and quantifies the information transfer between two processes [9]. 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. Given two processes x and y, the TE from y to x is shown in equation 1:

$$TE_{y\to x} = \sum_{x_{n+1},x_n,y_n} p(x_{n+1},x_n,y_n)\log\left(\frac{p(x_{n+1},x_n,y_n).p(x_n)}{p(x_n,y_n).p(x_{n+1},x_n)}\right) \quad (1)$$

Here, x_n denotes the status (value) of signal/system x at time n, y_n denotes the status of signal y at time n and x_{n+1} denotes the status of signal x at time $n+1$. Due to the finite size and non-stationarity of data, TE matrices usually contain much noise. In the existing literature, noise/bias has been removed from the estimate of TE by subtracting the average transfer entropy from y to x using shuffled version of y denoted by $< TE_{y_{shuffle}\rightarrow x} >$, over several shuffles. $y_{shuffle}$ contains the same symbol as in y but those symbols are rearranged in a randomly shuffled order. The normalized TE is calculated from y to x with respect to the total information in sequence x itself. This will represent the relative amount of information transferred by y. The NTE is shown in equation 2 as follows [10]:

$$NTE_{y\rightarrow x} = \frac{TE_{y\rightarrow x} - < TE_{y_{shuffle}\rightarrow x} >}{H(x_{n+1}|x_n)} \quad (2)$$

In equation 2, $H(x_{n+1}|x_n)$ represents the conditional entropy of process x at time $n+1$ given its value at time n as shown in equation 3.

$$H(x_{n+1}|x_n) = -\sum_{x_{n+1},x_n} p(x_{n+1}, x_n)\log\frac{p(x_{n+1}, x_n)}{p(x_n)} \quad (3)$$

NTE is in the range $0 \leq NTE_{y\rightarrow x} \leq 1$. NTE is 0 when y transfers no information to x, and is 1 when y transfers maximal information to x. In the present study, the FBNs are constructed by computing the NTE between EEG channels.

3. METHODS

3.1 Participants and EEG Data Acquisitions

Ten healthy, right-handed adult (seven males, three females; age range 22-59) academic/professional staff and students of the University of South Australia volunteered to participate in this study. The experiments were conducted at the Cognitive Neuroengineering Laboratory of the University of South Australia. All participants reported normal hearing, normal or corrected-to-normal vision without any history of psychological, neurological or psychiatric disorders. EEG data were acquired at a sampling rate of 1000 Hz through a 40 channel Compumedics Neuroscan Nuamps amplifier using Curry 7 software. Prior to data collection, each participant was fitted with an appropriate sized 32 channels Quikcap. The 30 electrode sites used 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 three different brain states: eyes open (baseline), visual search and Web search interaction conditions. All stimulus onsets and participant responses were time-marked on the EEG record using Compumedics Neuroscan STIM 2 software and with the help of interaction logs from screen capture software Camtasia Studio.

3.2 Cognitive Tasks

Continuous EEG data was recorded while participants undertook the following computer-based experimental tasks. Stimuli were presented via STIM software for the first two tasks (i.e. 3.2.1 and 3.2.2 discussed below). For task 3.2.3, participants were provided with an Internet-connected computer. Users' Web search interaction sequences (e.g. mouse and keyboard activity; visited and bookmarked URLs) were recorded using Camtasia Studio software.

3.2.1 Eyes Open/Eyes Closed (2 minutes each)

To obtain baseline brain activity in Eyes Open (EOP) state, participants were asked to stare at a blue color fixation star comfortably on the STIM computer monitor for 2 minutes. They were then asked to close their eyes and sit calmly for a further two minutes. In the current study, only the EOP data were used for analysis and comparison with the search related brain activity.

3.2.2 Visual Search (VS) Task (approx. 2 minutes)

In this task, participants were asked to identify a target object from an array of distractor targets. For example, in Figure 1, the top red letter is the primary target. The participants would be required to press 'y' if the target is present amongst the black distractor array, or 'n' if the target is absent.

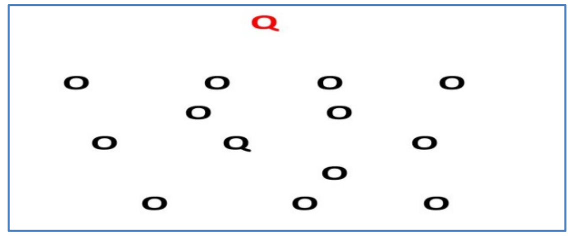

Figure 1. An example of visual search

3.2.3 Web Search Task (approx. 5-10 minutes)

The participants were instructed to search information on the Web based on three provided topic areas. They were free to use any Web browser (e.g. Internet Explorer, Google Chrome, Mozilla Firefox) and any search engine (e.g. Google, Yahoo). Participants were also free to choose the source of information. The search questions provided for the three different scenarios are given below:

Scenario 1: *Your employer has just told you that he is going to give you a new company car and asked you to choose one. The only restrictions are that the car must be red and be reasonably fuel efficient but it cannot be a European brand.*

Scenario 2: *While walking in the scrub in the Adelaide Hills you get bitten by what appears to be a tick. Should you go to the hospital Emergency Department ASAP? YES/NO and WHY?*

Scenario 3: *You've decided that you want to see a movie at the cinema. What movie do you decide to see, which session, which cinema and why?*

3.3 EEG Signal Pre-processing

From the collected EEG recordings of ten participants, two were excluded based on excessive residual artifacts such as muscle movements. Pre-processing of the remaining eight participants' EEG data was done by applying 1-70 Hz band pass filter 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 artifacts were then removed using principal component analysis (PCA). Bad blocks were removed manually.

3.4 Analysis Framework

In the Web search interaction, the tasks were divided into three subtasks: Query formulation (Q), viewing of search result List (L) and reading the each individual Content page (C) as shown in Figure 2. Subtasks were time marked on the EEG signals using the captured interaction logs (key and mouse strokes) of Camtasia Studio software, although we did not distinguish between the subtasks of each individual task. EEG data were then divided into 2 second epochs for each subtask (if greater than 2 seconds). Those epochs were then averaged for each subtask level to produce one epoch of averaged data level. In order to compare search features with the baseline (EOP), 50 chunks of EEG data of two seconds duration were randomly selected from the EOP data, and then averaged. Visual search data was also considered as baseline search activity by making 2 second epochs from the stimulus onsets, then averaging into a single 2 second averaged data epoch. Averaged EEG data epoch during EOP, VS, Q, L and C were then used for the computation of NTE matrices, where each cell of the NTE matrices represents the NTE value from one electrode to another. In the case of FBNs, scalp electrodes are considered as vertices/nodes and the connections/links between electrodes are measured using NTE [8]. The constructed NTE matrices were then binarized for the analysis using different types of complex network metrics. The following complex network metrics were used: connectivity density representing the actual number of edges as a proportion to the total number of possible edges [11] which is the simplest estimator of physical cost of a network and basically used to find the global interaction pattern/magnitude of the network; node degree of directed network represents the total of incoming and outgoing edges [11] which is basically used to find hub node/region of a network. The data, information processing and associated computational steps are illustrated in Figure 2.

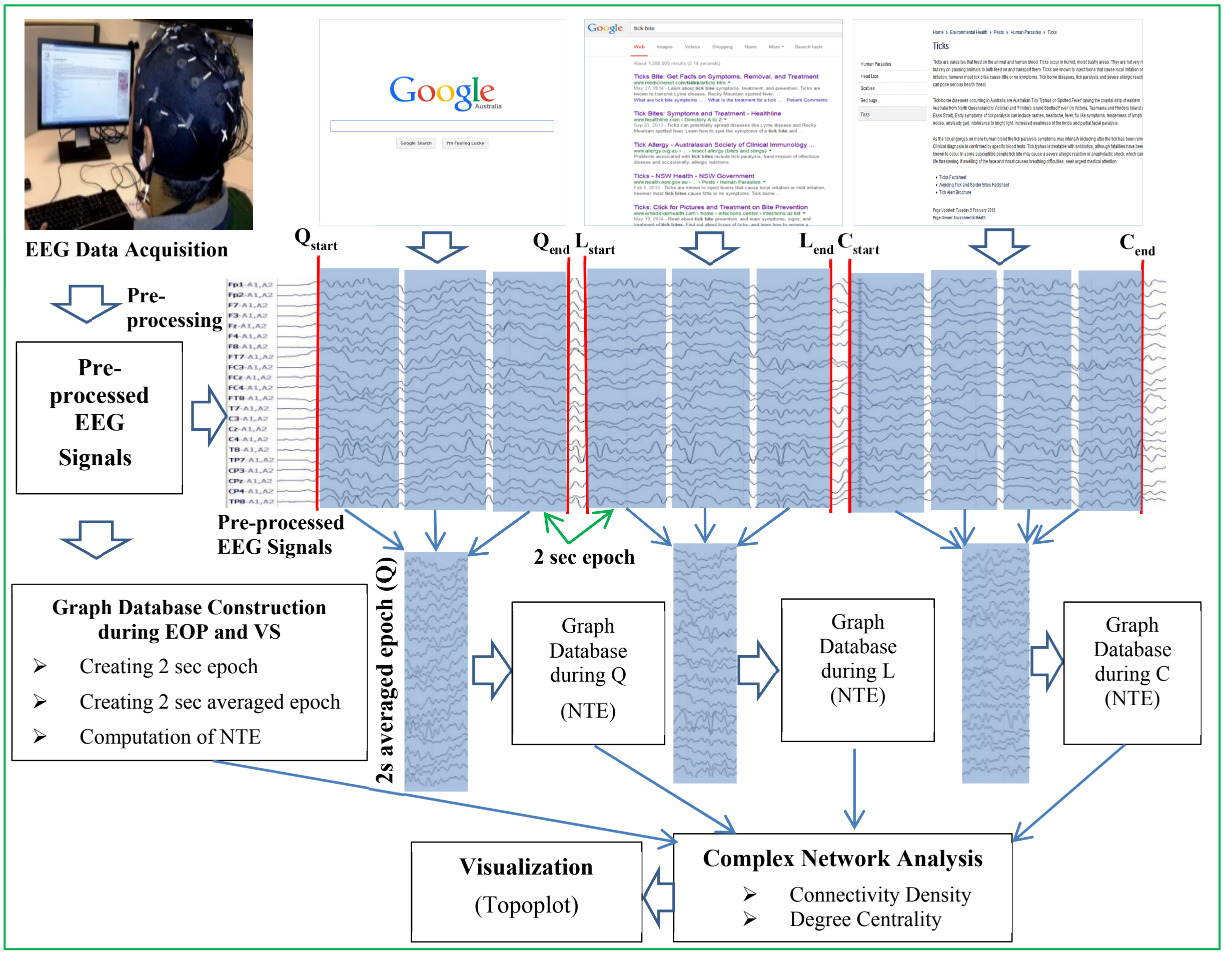

Figure 2. Transfer Entropy Analysis Framework for Web Search (TEAF-WS)

4. RESULTS AND DISCUSSION

4.1 Connectivity Density

The group averaged connectivity density of different brain states (EOP, VS, Q, L and C) was calculated and shown in Figure 3. To calculate the group averaged connectivity density, connectivity density of each individual participant was calculated then averaged across participants. As EOP was the baseline cognitive state, it had the least connectivity density compared to Web search task stages (Q, L, and C). This suggests that higher connectivity density during Q, L and, C is directly task related. That Q has higher connectivity density than L or C further supports this given that query formulation requires the execution of a number of simultaneous processes (e.g. defining query terms, viewing search interface, typing etc.).

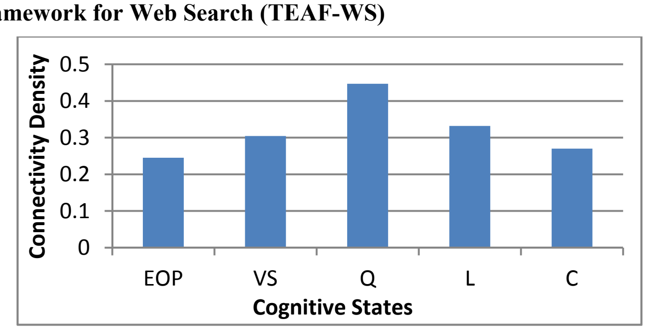

Figure 3. Connectivity density during different brain states

4.2 Topoplot using Degree Centrality

The group averaged degree centrality of all electrodes for each brain state was plotted and displayed in Figure 4 using the

EEGLAB Topoplot function [12]. Topoplot function visualizes a topographic map of a scalp data field in a 2-D circular view. To visualize the subtle variation of degree centrality value in different brain states, the color map scale of Topoplot was customized such that a color map scale is used from minimum degree centrality value to maximum degree centrality value among the degree centrality value of all the electrodes of all the brain states [12]; thus blue represents the minimum degree centrality value and red the maximum degree centrality value. Of note, all topoplots showed clear activity which is reflective of the degree of engagement for each task; that is, the visual search condition shows greater engagement than the eyes open condition, while the list reading condition shows greater engagement than the content reading condition. In the case of eyes open versus visual search, this is easily explainable – a visual search task requires focused, more intense visual attention than simply staring at a fixation star. Similarly, the button press response requirement of the visual search task elicited higher activity in motor areas (FCz, Cz, C4) than the eyes open condition. The differences between list and content reading are also explainable, albeit conjecturally, on an attentional/focus basis; that is, content reading has been "filtered" via the list process, therefore is focused externally by this process such that content reading requires less internal focus through reduced decision-making requirements. Interestingly, the similarities in processing between the visual search and contents reading tasks suggest that the two tasks share common cortical regions in the execution of those tasks. There are, however, some obvious differences between content and list reading, with list reading eliciting higher activity at CP4 and TP8 whereas content reading exhibited higher midline activity at CPz and Pz. However, in the case of the query formulation task, the high activity is most likely a reflection of multiple processes contaminating the averaging process. Further work is currently being conducted to divide this task into smaller sub-tasks so that movement, language, decision-making, and attentional processes can be further delineated during this query formation phase.

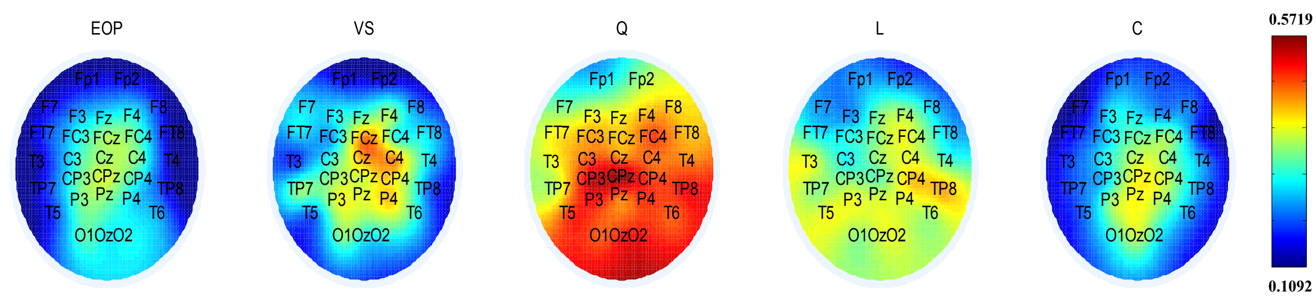

Figure 4. Topoplot during different brain states using degree centrality

5. CONCLUSION

The key contribution of this study is the construction of functional brain networks using NTE during different stages of Web searching which enabled detailed investigation of brain function during Web searching. This study quantitatively identified that during Web searching the information transfer increases in brain networks when compared to baseline. This study also demonstrated that brain activity during different Web search task stages is not the same. This study may have implications to examine the effects of cognitive abilities on information search behaviour/processes and search task performance/outcomes, thus it could allow an adaptive information retrieval system to better personalize its interaction with users. Future work will increase the sample size and consider the effect of task complexity in the experimental design.

6. REFERENCES

[1] Du, J.T.: Cognitive coordinating behaviors in multitasking web search. Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval, pp. 1117-1118. ACM (2011)

[2] Du, J.T., Spink, A.: Toward a web search model: Integrating multitasking, cognitive coordination, and cognitive shifts. Journal of the American Society for Information Science and Technology 62, 1446-1472 (2011)

[3] Scholer, F., Kelly, D., Wu, W.-C., Lee, H.S., Webber, W.: The effect of threshold priming and need for cognition on relevance calibration and assessment. Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval, pp. 623-632. ACM (2013)

[4] Kim, Y.M., Rieh, S.Y.: Dual task performance as a measure for mental effort in library searching and web searching. In Proceeding of the 68th Annual Meeting of the American Society for Information Science & Technology 42 (2005)

[5] Gwizdka, J.: Distribution of Cognitive Load in Web Search. Journal of the American Society for Information Science and Technology 61, 2167-2187 (2010)

[6] Cole, M.J., Gwizdka, J., Lui, C., Belkin, N.J.: Dynamic Assesment of Information Acquisition Effort During Interactive Search. Proceedings of the American Society for Information Science and Technology 48, 1-10 (2011)

[7] Gwizdka, J., Mostafa, J., Moshfeghi, Y., Bergman, O., Pollick, F.E.: Applications of neuroimaging in information science: Challenges and opportunities. Proceedings of the American Society for Information Science and Technology 50, 1-4 (2013)

[8] Shovon, M.H.I., Nandagopal, D.N., Vijayalakshmi, R., Du, J.T., Cocks, B.: Transfer Entropy and Information Flow Patterns in Functional Brain Networks during Cognitive Activity. In Neural Information Processing, Lecture Notes in Computer Science (LNCS 8834), Part I, 1-10 (2014)

[9] Schreiber, T.: Measuring information transfer. Physical review letters 85, 461-464 (2000)

[10] Gourévitch, B., Eggermont, J.J.: Evaluating information transfer between auditory cortical neurons. Journal of Neurophysiology 97, 2533-2543 (2007)

[11] Rubinov, M., Sporns, O.: Complex network measures of brain connectivity: uses and interpretations. Neuroimage 52, 1059-1069 (2010)

[12] Delorme, A., Makeig, S.: EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of neuroscience methods 134, 9-21 (2004).