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# Predicting Normal People's Reaction Time based on Hippocampal Local Efficiency During a Memory-Guided Attention Task

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## ABSTRACT

**Background:** There are some convincing shreds of evidence indicating that memory can direct attention. The local efficiency of an area in the brain, as a quantitative feature in a complex network, indicates how the surrounding nodes can transfer the information when a specific node is omitted. This feature is a scale for measuring efficient integration of information in the brain.
**Objectives:** The purpose of the present study is to predict the reaction time using the local efficiency variable while doing memory-guided attention task.
**Materials and Methods:** The fMRI database of a research done in New York University during a visual search task was used for this study. Thirty-five right-handed healthy participants (51% female, mean age= 21.7 years) were recruited at New York University. SPM was used for pre-processing fMRI images, and CONN was used for calculating the values of local efficiency. SPSS was also used for statistical analysis of the study.
**Results:** Results of the study revealed that local efficiency of the right hippocampus can positively predict the reaction time during memory-guided attention tasks.
**Conclusion:** The findings of the study demonstrated that the hippocampus area has a significant role in the performance of memory-guided attention, and this significant role of the hippocampus reveals that long-term memory uses the hippocampus and affects the movement and attention of eyes on the target.

**Keywords:** Reaction Time; Memory; Hippocampus; Attention; Functional Neuroimaging



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## Introduction

Attention is controlling the mind clearly and lively, concentrating on one thought (or a chain of thoughts) among a number of simultaneous subjects that are possible. In other words, attention is a performance by which, among the large sources of information gathered through senses, saved memory, and other cognitive processes, a limited amount of information is actively processed [1]. Attention consists of conscious and unconscious processes. Studying unconscious processes is more difficult than studying conscious processes because subjects are not consciously aware of what they are actually doing. In fact, even a simple thing or a picture or a set of them can direct the visual attention and perceptual sensitivity [2].

On the other hand, the visual ability of humans, despite being like a supercomputer, is limited because of the restriction of attention [3]. Memory, as the conductor of attention, can be the connector of the real-world performance and the limited capacity of attention. After all, although analyzing the effects of memory on attention is rather a new topic for study [4], there is convincing evidence indicating that memory can direct attention. The Hippocampus can rapidly encode our memory of events, which are flexible and rich in contextual details [5]. Long-term memory uses the hippocampus for complex scenes [6,7]. In normal and healthy people, the hippocampus and striatum memory systems can simultaneously regain information [8]. However, the different roles of these two parts are confirmed by studying rats and human [9,10].

Simultaneous technology developments have created a variety of databases in biological, technological, social, and other scientific realms. Attempts at describing these data in the last decade have led to the emergence of an interdisciplinary approach for studying complex systems [11,12]. This approach called, complex network analysis describes important features of complex systems by quantification of the topological representation of every part of the network [13]. In fact, in recent years, database of large complex systems, providing availability, flexibility, and high quality, has resulted in a basic concept that basically different complex systems often share specific organizational rules and these features can be quantified with the same parameters [14]. In other words, most of the complex systems show similar behaviors in the macroscopic scale despite the microscopic differences in the elements and transactional mechanisms. In network science, methodological advances have provided great help in determining other topological complex systems such as global efficiency, local efficiency, centrality, and the distribution of network hubs – most of which have now been measured in the brain [13].

Complex network analysis owes its origin to graph theory [15]. Graph theory introduces a number of rules for the representation of complex networks that can be used to describe any kind of network and the underlying connections among these parts. The graph is a mathematical representation of the real world of complex systems defined by a set of nodes and edges which it represent the relationship between the pairs of nodes. The nodes represent regions of the brain and edges represent relations and connections among the regions of the brain. The analysis of graph theory can provide a useful framework for understanding the network structure of the brain [13].

Complex networks are organized structures and features in different levels that have interactions with the upper and lower levels and in their nature they depict systematic rules, different kinds of symmetries, and consistent orders and behaviors [16]. Complex systems often share specific organizational rules and these features can be quantified by the same parameters. Local efficiency is one of the most important and prevailing features in complex network analysis. Local efficiency of a node explains how the surrounding nodes transfer information when a specific node is omitted. This variable is a quantitative scale for measuring fracture resistance [17]. Local efficiency index is a quantitative and numerical value that can be calculated by the following formula:

$$E_{loc} = \frac{1}{n}\sum_{i\in N} E_{loc,i} = \frac{1}{n}\sum_{i\in N} \frac{\sum_{j,h\,\epsilon N\,,j\neq i} a_{ij}a_{ih}\left[d_{jh}(N_i)\right]^{-1}}{k_i(k_i-1)}$$

For calculating the local efficiency of a node, first the connections and sub nodes of a particular node are selected. After, omitting that particular node, the shortest routes among all remaining nodes are calculated. Finally, the reversed average of all shortest routes of the nodes that had connections with that particular node is calculated. Local efficiency is a value between 0 and 1. In the analysis of functional connections in the brain network, higher numerical values of local efficiency indicate the independent and separate processes in the brain [17]. In the study by Stanely *et al.*, features of complex networks were used to predict the performances of subjects in an n-back working memory task in two young and old age groups [18]. Results of this study revealed that deduction of local efficiency during the working memory task resulted in better performance of working memory in both age groups. On the other hand, an increase in the overall efficiency in the young group had correlation with better performance of working memory, whereas in the old group, an increase in the overall efficiency had an inverse relationship with their performance in the task.

In their study, Geib *et al.* used elements of complex network features to analyze the hippocampus in vivid and vague memories [19]. Results indicated that the right hippocampus has better connection efficiency (shorter route) in vague memories. Also, during the process of turning vague memories into vivid ones, these features are reorganized.

The purpose of the present study is to evaluate prediction of the reaction time using the value of local efficiency while doing a memory-guided attention task.

## Materials and Methods

For this study, the recently established research fMRI database of the University of New York was used. The present research was authorized to be done on human samples by research the committee of New York University in 2016 [2].

### *Research tools*

Visual Search Task: Visual search task is a type of perceptual task requiring attention that typically involves an active scan of the visual environment of a particular object or feature (the target) among other objects or features (the distracters). Visual search can take place with or without eye movements.

The task used in the study by Goldfarb et al. was an expanded version of the visual search task presented by Jeremy Shen in 2007. Shen's visual search task is based on the paradigm of contextual cueing learning. In this task, after 24 practicing trials, subjects are supposed to do a visual search task in which they are asked to find the direction of the letter T among other distracters of letters

L. This task was given in 576 panels (within 6 runs). After the fixation screen, subjects have a maximum of 4 seconds to find the letter T on the screen and then determine its direction by pressing on related keys. In the next screen, the subject is given a feedback. If the direction is correct then, according to the time of answering, a score from 1 to 10 is given to the subject. The quicker the answer, the higher the score is. In case the answer is wrong or is not given within 4 seconds, a score of -10 is given to the subject. There are two conditions for the placement of our target among the distracters: In the first condition (No Cue), the target and the distracters do not involve the subjects' memory and just evaluate the performance of their attention. In the second condition of the task [episodic memory-guided attention phase (Contextualized Cue or CC)], distracters are presented in only one place. The distracters are signs for finding the position of the letter T, although they do not help find its direction. This condition of the task involves the subjects' episodic memory and their attention performance. Previous studies have indicated that in this condition, learning happens by contextual cueing paradigm [2].

***Data collection procedure***

Based on the research by Goldfarb et al, one fMRI scan for each performance of the subjects was recorded while the subjects were doing their tasks, and by doing so there were six fMRI scans. Also, one MRI image from the subjects' brain was taken. The scans were interleaved and they were taken with two seconds of repetition time (TR). The output of the search task for each panel of task consists of an answering time and a score for the subject [2].

***Selected brain parts***

For this study, the left and the right hippocampus and the striatum (putamen and caudate) were selected.

***Data analysis methods***

SPM12 was used for preprocessing fMRI data. CONN toolbox from MATLAB was used for analyzing the features of complex networks. This toolbox is a platform for analysis and representation of schematics and, functional connections in fMRI data. Simultaneous regression task in SPSS 24 was also used to find out whether or not the values of local efficiencies of the brain parts can predict the answering time of subjects during the search task.

## Results

In this research, 35 healthy and right-handed people (51% female with an average age of 21.7) participated. The local efficiency indices were calculated for the hippocampus (left and right) and the striatum (left and right putamen and left and right caudate) by using CONN toolbox for each subject and then multiple regression analysis was used to evaluate the degree of predictability. Due to personal differences, the variable which was dependent on the value gained by the subtraction of answering time of each subject in episodic memory-guided attention phase from answering time of each subject in the no-cue phase was considered. The results of the regression analysis are given in Table 1.

**Table 1.** Results of multiple regression analysis on the local efficiency index

| | Correlation Coefficient | R-squared | Unstandardized (B) Regression Coefficient | t statistic | *p-value* |
|---|---|---|---|---|---|
| (constant) | 0.668 | 0.45 | | 0.675 | 0.51 |
| Local efficiency of right caudate | | | -226.07 | -0.81 | NS |
| Local efficiency of left caudate | | | 612.15 | 1.82 | NS |
| Local efficiency of right putamen | | | -366.94 | -1.29 | NS |
| Local efficiency of left putamen | | | -519.54 | -1.76 | NS |
| Local efficiency of right hippocampus | | | 570.35 | 2.87 | 0.01 |
| Local efficiency of left hippocampus | | | -362.15 | -246 | 0.05 |
| Dependent variable: RT in memory task – RT in no-cue condition | | | | | |

Table 1 shows that variable of local efficiency in the hippocampus, caudate, and putamen areas with a multiple correlation coefficient of 0.66 have been able to depict about 45% of the differences of reaction time (RT) during the memory-guided attention task in contextual cueing phase. Here local efficiency of the left hippocampus and local efficiency of the right hippocampus could negatively and positively predict the RT during the memory task, respectively.

## Discussion

Complex cognitive networks of the brain can be analyzed using the interactions between its functional networks. In recent years, effort has have been put into evaluating these interactions, although a lot of challenges still remain in finding better methods for such studies. The present study was performed with the purpose of analyzing the ability of predictability of people's RT using the values of local efficiency while doing a memory-guided attention task. The topological structure of networks has a direct correlation with local efficiency index [13]. This index is a criterion for measuring efficient integration of information in the brain. In the studies performed in these areas, local efficiency provides a criterion giving the idea of how information is integrated efficiently into the surrounding nodes. In the present study about predicting RT by local efficiency, multiple regression analysis showed that the local efficiency index of the hippocampus can predict the answering time of subjects during the memory-guided attention task. The local efficiency of the hippocampus that can predict people's RT while doing an episodic memory-guided task is probably due to important role of the hippocampus in this kind of memory. As mentioned before, previous studies indicated that the hippocampus area is the area of episodic memory [5]. The findings of the present study reveal that the hippocampus area has a vital role in the function of episodic memory-guided attention and this role shows that long-term memory uses the hippocampus. Therefore, attention and the movements of the eyes on targets, even in the absence of an explicit call, are affected. Also, the present study indicated that the value of local efficiency can be used as an efficient variable for predicting people's performances during cognitive tasks.

## Conclusion

The results of this study indicated the considerable role of memory in the attention system. It is suggested that the impact of old memories to explain, describe, and predict the behavior of humans and animals should be taken into consideration. On the other hand, the complex network properties can be used for representations of cognitive performance.

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## Conflict of Interest

The authors have no conflict of interest.

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