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Leveraging Initial Cognitive Load to Predict User Response to Complex Visual Tasks

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Abstract **-** In this study, we were able to show how cognitive load measurement during the initiation of a complex visual task can predict user response. We measured cognitive load using pupil size and microsaccade rate. The initial phase of task was defined as the first 25 percent of the trial Reaction Time (RT), which was variable up to 50 seconds. The complex visual task entailed a set of twelve words that could be grouped based into 1, 2, or 3 categories or sets, e.g., the words bed, pillow, headboard, etc. can be grouped into a single set that is bedroom. We found a significant correlation between initial cognitive load and final user response to the task. This study provides new insights into the initial cognitive processes that would have practical applications in adaptive user interface design, early warning controls, and detection in human performance.

Keywords**:** Visual Tasks, Cognitive Load, Eye Movement, Initial Response

1. Introduction

Computer interfaces are intended to cater to users with varying needs, preferences, and goals. A good interface is tailored to or needs to adapt to the user's tasks, or the user's work efficiency and comfort can be strongly reduced by poorly designed interfaces. This underscores the importance of Human-Computer Interaction (HCI) research focused on optimizing user performance by leveraging advanced measurement techniques. Tracking user response during tasks and measuring cognitive load is one such useful method in HCI research. Cognitive load measurement allows us to gain insight into user performance and use it to adapt interface design tailored to specific tasks. The complexity of interface and task can affect user visual attention and response due to different levels of cognitive load [28]. One important type of cognitive measurement is task performance [5], [33]. Performance measures indicate how efficiently the user is performing a specific task e.g., measuring lane departure, or steering wheel used in a driving simulator [23], [39], finding targets in visual search [6], or solving a math problem [14].

In this study, we use eye tracking data to estimate cognitive load during a text-viewing task. The text-viewing task is a new presentation format that was termed by Attar et al. who provided evidence of the effectiveness of measuring eye movement data related to user response without the influence of the reading process [21]. In a text-viewing task, unlike reading a passage, the user has the freedom to process words in any order, where processing of the previous word in this format is not necessary for viewing the next word. The words are examined by the user individually in terms of rhythm and linguistic content wherein the words can be semantically grouped in either one, two, or three categories.

In the present study, we measured participants' cognitive load across text-viewing tasks, where the number of categories is different. We investigated the interaction between pupil size and microsaccade rates to detect differences in response across participants at the initiation of the task as an effective predictor of task response. This contrasts with previous approaches that measure cognitive load during the entirety of the task, or more commonly, at task completion. We were able to predict the response of the user by measuring cognitive load at the onset of the task.

2. Related Work

Monitoring the cognitive load of a user during a task can be used to predict user response. Previous studies analyzed observers' pupil sizes during the early period of the search task and found that pupil size increased over the course of the search, which they attributed this finding to accumulating cognitive load [6]. This conclusion was consistent with follower studies that proposed a close link between cognitive load and search efficiency [1], [4], [20], [25], [40]. The early increase in cognitive load can be associated with more efficient search, indicating a significant role of cognitive load in the search process [22]. Previous models for studying the comprehension process during reading have attempted to predict readers' comprehension level and language skill from multiple eye-movement measures. For example, Martínez-Gómez and Aizawa found characteristic features in eye-tracking data of reading task that indicated a subject's level of understanding and English language skill [27].

While it is valuable to understand behavior or response when users' complete tasks, it is usually measured through the entirety of the task, or at the end of the task with user manual input response (e.g., keyboard, mouse), rather than at the initiation of the task. Such manual responses may not accurately reflect cognitive load. A study by Mock et al. explored the potential of using touch sensor data to predict user states in learning scenarios [26]. They were able to use touchscreen data to improve automatic prediction of high levels of cognitive load. However, when they classified the data based on the task difficulty, they reported that they were not able to provide any significant result that proved touch as a feature for predicting user states. This finding was similar to the study by Boyer et al. when they explored the question of detecting anomalous attention states during transition to high cognitive load, following an extended period of boredom using fNIRS in the context of a missile defense simulation, using three missile or six missile conditions [13]. The fNIRS data were unable to capture the validated increase in workload when subjects were asked to perform the task that has six missile conditions. They also found no significant difference in their cognitive load result for difficulty between the two conditions. The question of whether we can find an interval of a task's time, where the data can be an accurate prediction of the user's response, has not gained much attention to date. Whether the studies use touch screen, fNIRS, eye-tracking data to measure performance and subjective cognitive load, a further work is needed to better understand the relationship between cognitive load and predicting task performance. A recent study has investigated the difference between sudden and gradual workload transitions in terms of performance during a task but not at the initial of the task [41]. Being able to determine the cognitive load of a task at the initial of the task can be used to improve those interfaces that are sensitive to time. Detecting cognitive load at the initial of the task can help adaptive interfaces to be well timed with changes and will help users to feel in control while using an interface.

3. Eye Movement Overview

Without interfering with the user performing a task, we can understand the user's performance by using eye movement as an implicit input device during computer-based tasks. An eye-tracker is one such non-invasive device that leverages eye-movement information as quantitative data during visual tasks. This gives insight to researchers on user cognition with precise moment-to-moment measurement during various tasks. Pupillometry is used to measure the attentional and most behavioral activities during visual tasks with the eye-tracker [2]. Several studies in HCI research have used pupil size as an indicator of cognitive load (e.g., [18], [35]), to measure working memory load during visual search [6], [7], or to distinguish the age of subjects and their vision health condition [8]. Eye-tracking technology can gather other inputs in addition to pupil size to measure cognitive load, such as saccade characteristics [16], fixations [21], and microsaccades [17]. When a fixation occurs, our eyes produce fixational eye movements that include a sequence of microsaccades. These microsaccades produce neural modulation that facilitates spatial and temporal integration in the visual system. This allows synchronization among different cortical structures, as well as supporting perception [12], [34], [36], [38].

Many studies have associated microsaccades to perception and attention allocation [29], [30], [37], task difficulty [24], and working memory [19]. The analysis of microsaccades and pupil size has been investigated in very limited visual search conditions. Researchers in [3] used a visual search task with target selection, where subjects need to press a button when they find the target. They found that the human pupil is associated with perceptual mental activities related to decision making and user’s detecting of the target after the visual search. The pupil responds by dilating to visual detection and the amount of dilation depends on whether the user presses the button to report finding the target. The researchers also found that more microsaccades occurred for those targets. However, their study only examined visual search tasks around a target selection event. Furthermore, pupil size and microsaccade have been studied separately to examine their relationship with cognitive load and attention. To the best of our knowledge, comparing task-evoked pupillary and microsaccade rate as indication of cognitive load started only a few years ago [9], [10], [11], [37]. These studies’ extensively contributing to the study of microsaccades and pupil size and their relationship to cognitive load. However, they have not explored prediction of user response in the early stage of the decision-making process. In this study, we achieve this by examining microsaccade rate and pupil size at the initiation of the task to predict the participant response, rather than as an indicator of the “current” cognitive load or “task difficulty”.

4. Experiment

In this study, we used data collected previously by Attar et al. [21]. Their study using text-viewing task showed that it can eliminate the impact factor of reading format in conventional reading. Each display contained 12 words located in random positions with a minimum distance of 5 degrees between them. Subjects examined these words individually in terms of rhythm and morphological content.

4.1. Experimental Setup

Eye movements were tracked and recorded using an SR Research EyeLink-2k system that was set to 1000 Hz sampling frequency. A 22-inch ViewSonic LCD monitor was used for the study with a resolution of 1024 x 768 pixels and 75 Hz refresh rate. Participants used a keyboard to enter their responses. Black Courier font at size 20pt was used with a grey background color for the total of 42 stimuli used in the text-viewing task. The average length of words in any stimuli was 6.4 letters (minimum = 3 letters, maximum = 13 letters). A MATLAB script generated all the stimuli (1024 x 768 pixels) for the task. 30 different word categories were generated (e.g., supermarket, bakery, farm, hospital, etc.). Every trial had 12 words that belonged to one, two, or three categories. For example, words such as “pastry”, "oven", and "apron" belonged to one category "bakery", whereas words such as "horse", "patient", and "medicine" belonged to two categories "farm" and "hospital". To avoid any confusion when the user explored the words in a trial, every category had its unique set of words. Figure 1 shows an example of a trial that has one category.

Fig. 1: A Sample of text-viewing task with one category "supermarket"

4.2. Procedure

Twenty one subjects who were native English speakers aged between 18-32 (14 females, ave. 23.23, std. 4.08) years old participated in the study. All had normal or corrected-to-normal vision and were naive to the purpose of the study. Subjects had one block of practice before they started the experiment. All the subjects examined the 42 stimuli in the experiment but in a random order of trials for each subject. During each trial, subjects had to identify the number of categories to which the 12 words belonged and respond by pressing the numbers (1, 2 or 3) on the keypad. After subjects responded, a feedback sound was played to indicate whether the subject's answer was correct or incorrect before a new trial appeared. The next trial would begin once subjects pressed any of those keys or a timeout of 50 seconds transpired.

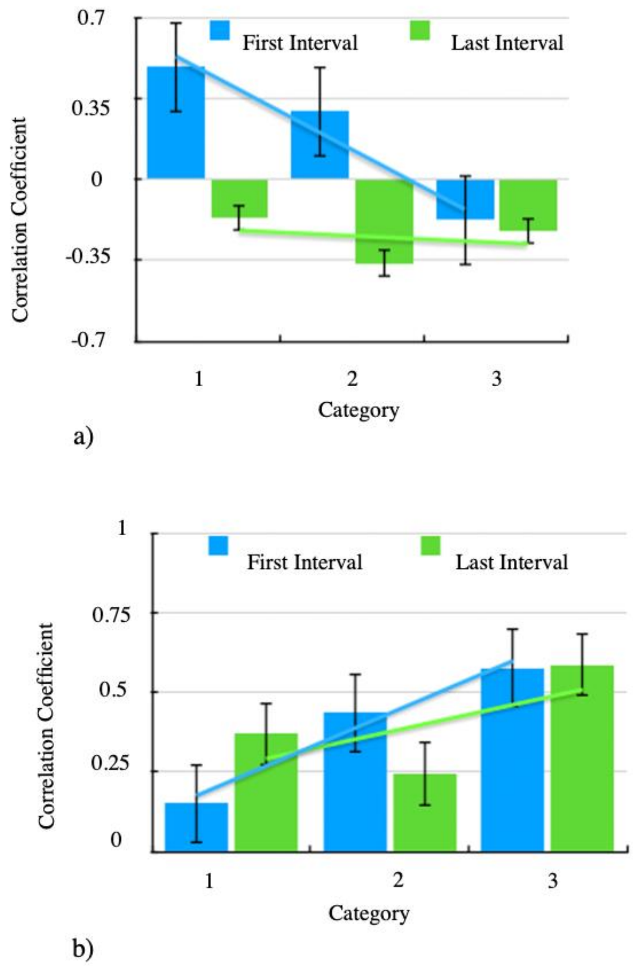

Fig. 2:a) Correlation between the change in pupil size across the three categories and RT in the first interval and last interval. Error bars indicate standard error of the mean. b) Correlation between the microsaccade rate across the three categories and RT in the first interval and last interval. Error bars indicate standard error of the mean, and straight lines indicate the result of linear regression.

4.2. Data Analysis

We used the raw data of nineteen native English-speaking subjects who completed a text-viewing task that had thirteen trials per category. We eliminated 2 subjects from the study as they did not perform any trials with 3 categories in the 42 trials total. Removing these two subjects prevented imbalance in the dataset. We only included in the analysis the correct responses for each category based on the assumption that data of incorrect responses contain more noise than informative data related to the number of categories in each trial [32]. The overall accuracy for participants for the 1-category, 2-categories and 3-categories trials were 90.16%, 82.4%, and 85.6%, respectively.

We used the algorithm developed by Engbert et al. to extract the saccade/microsaccade rate [31]. Then we used a Python script to extract other data such as the mean fixation duration and pupil size. The mean of saccade/microsaccade magnitudes, durations, and peak velocities were calculated for each subject and each trial separately along with the pupil size. Then, the change of the pupil size for all trials and microsaccade rate (rate of occurrence) in each category was calculated. To generate the microsaccade rate, we created saccade tables and calculated the onset, offset, peak velocity, horizontal component, vertical component, horizontal amplitude, and vertical amplitude. To generate the average change in pupil size, we measured the difference between the minimum and maximum pupil size for each epoch in the trial.

The choice of 50 seconds as the timeout for the text-viewing trials was taken from Attar et al. [21] in their optimal character recognition study as their experimental setup choice. This duration for the timeout was to make sure subjects had adequate time to complete the task. The averages of reaction times (RTs) for 1-category, 2-categories and 3-categories trials were 10.10 seconds (SD = 6.72), 13.52 (SD = 9), and 15.28 (SD = 8.66), respectively.

We tested the use of a fixed interval in a trial but found this strategy was inefficient in predicting user response, as each trial had a different RT. For example, if the fixed time of the length of the intervals is 1000ms, then the first interval will be the first 1000ms and the last interval will be the last 1000 of the trials. These two intervals of 1000ms will be analyzed based on their pupil size and microsaccade data. We tried four possible options of fixed times of the first and last intervals (1000ms, 2000ms, 3000ms, or 4000ms). For each subject, we separated the trials based on the number of categories. We computed the average of pupil size and microsaccade rates for every category per subject, then computed the average across all subjects for the first interval of the trials. We repeated the same computations for the last interval of the trials. The change of cognitive load across task categories was not significant for the first interval of the trial for pupil size (ps = 0.78) and microsaccade rate (ps = 0.21), nor for the last interval of the trial for pupil size (ps = 0.75) and microsaccade rate (ps = 0.45) for all the four fixed time durations across all the trials.

Therefore, our conclusion was that the length of the interval should be relative to the time to complete the task by the user. We divided every trial into four equal intervals based on individual trial's RT. We divided intervals into the following: the first interval is when the trial starts, the second and third are the center of the trial, and the last is when the user responded with the keyboard key. The averages of the change in pupil size and the microsaccade rate were calculated for the first and last intervals in each trial for all subjects separately.

5. Results

Two factors were used in the data analysis. The first was the factor called Interval, measuring pupil size or microsaccade rate during the first interval and the last interval of the task. The second factor was Category, which identifies one, two, or three categories in the task.

- A repeated measures two-way analysis of variance (ANOVA) using these two factors for the change in pupil size indicated a marginal effect of Interval, $F(1; 18) = 2.97$, $p = 0.062$ and a significant effect of Category, $F(1; 18) = 12.6605$, $p < .005$. The interaction between the two factors was also significant, $F(1; 18) = 9.17$, $p < .005$.
- We also computed a repeated measures two-way analysis of variance (ANOVA) using these two factors for the average of microsaccade rate, which indicated a significant effect of Interval, $F(1; 18) = 22.794$, $p < .005$ and a significant effect of Category, $F(1; 18) = 7.5256$, $p <.005$. The interaction between the two factors was also significant, $F(1; 18) = 4.2554$, $p <.05$.

The effects of these factors on the correlation between the change in pupil size and Response Time (RT) or the correlation between microsaccade rate and RT are shown in Figure 2. The study achieved strong results suggesting that the change in pupil size and the microsaccade rate can be sufficient in discriminating the user's responses during the initiation of the task. Moreover, it predicted their response without the need to use other features (e.g., fixation or saccades) or analyzing the data in the entire task. The difference in the change in pupil size during the first interval across subjects during three-category tasks mainly reflects changes in cognitive load that occurred during the initial interval of the task, with an inverse correlation of approximately r = -0.20, t(18) = -11.5325, p < .005. The increase in the difficulty of the task during trials with three categories likely resulted in the higher correlation as they entail higher cognitive load.

- We found a significant positive correlation between the average of microsaccade rate during the first interval in all the category scenarios r=0.4348, ts(18) = -11.9644, ps(18) < .005. The amount of attentional resources devoted to each task likely increased with the number of the categories. The increase in the microsaccade rate can thus be interpreted as subjects needing more attentional resources to immerse themselves in the task, especially for higher-order cognitive process tasks [15].
- The difference between the microsaccade rate between the first interval of the trial and the last interval was significant in tasks with all three categories: ts(18) = 2.2057, ps(18) <.005 as shown in Figure 3.

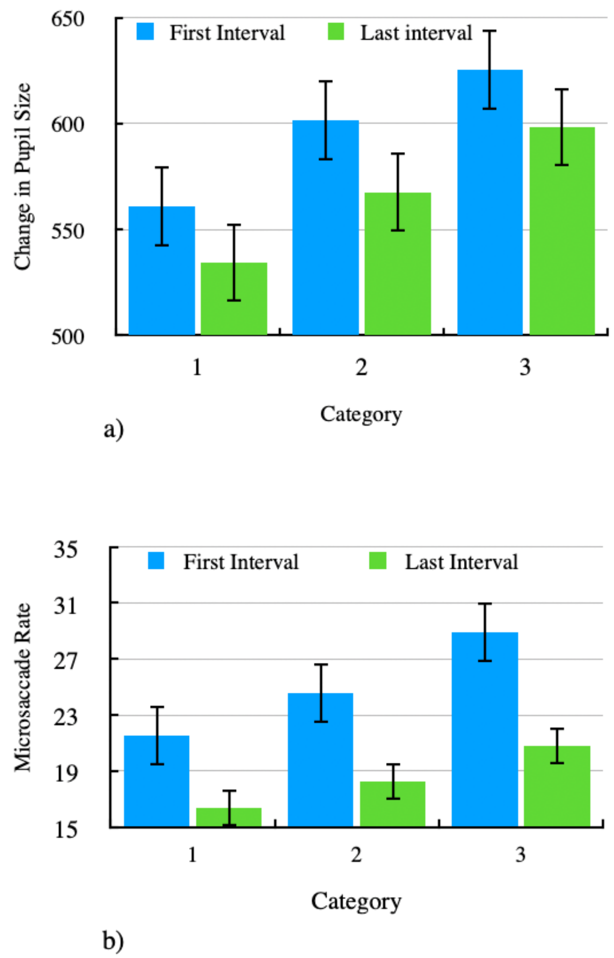

Fig. 3: a) Average number of the change in pupil size and, b) average number of microsaccade rate. Both results are across subjects during the different numbers of categories at the initial interval and the last interval of the task. Error bars indicate standard error of the mean..

6. Discussion

We only studied the first interval to support our hypothesis of predicting user response after dividing into 4-time intervals. We compared it with the last interval because it is where the user response usually happens and where the cognitive load level correlates with the user decision-making and behavior [2, 13, 26]. The intervals in the middle were not included in the analysis as it did not help our hypothesis of user task prediction at the initiation of the task. Adding the middle interval to the analysis would add confusion to our goal that the user response can be predicted at the onset of a task. The choice of dividing the intervals by four was to give a sufficient interval duration for the initial of the task (first interval) and the response time (last interval) and giving twice that duration to the performance of the task itself (two middle intervals). Therefore, the two middle intervals are located after the start of the task and before the user makes any response. In order to justify the choice of our length interval, we performed a pre analysis for the data, where we analyzed the first and the last of the trials using four different time frames ranging from 1000 ms to 4000 ms. The result from this pre-analysis showed that the response of the user should rather be detected when the duration time of the interval is relative to the RT of the trial. This approach was intended to highlight the fact that measuring the initial behavior was able to be predicted when the interval length was variable and not fixed across trials. The length of the initial interval should be further studied to determine a threshold for the interval duration that predicts the user response. One possible explanation of why a fixed length was not a successful approach could be because of the nature of the text-viewing task being measured. Measuring several tasks that required different visual attention levels can reveal more information about the initial of the task. Also, perhaps the earliest pupil size and microsaccade rate in the first 1000ms to 4000ms are driven by saliency or general interest, and user behavior-related pupil size and microsaccade rate are made later in the initial viewing.

6. Conclusion

This study gives us a more comprehensive understanding of cognitive load and how it can be leveraged to accurately predict user response during complex visual tasks. We studied cognitive load in the initial phase of a text-viewing task to find a significant correlation between initial cognitive load and the user's final response. We measured cognitive load using pupil size and microsaccade rate during the initial 1/4th of the user task (variable up to 50 seconds). We then analyzed the initial cognitive load to the type of answer the user provided to the experiment. Unlike previous studies which have focused heavily on cognitive load measurement throughout or at the end of task completion, this new approach shows that initial cognitive load measurement is sufficient. Furthermore, measuring cognitive load throughout or at the end is susceptible to other variables such as arousal of finding the answer, distraction, other confounding factors, and reduces the influence of non-related factors on eye tracking data.

This new approach can be extended and replicated for different visual task scenarios and evaluated against cognitive load measurement throughout the task. This study allows us to better understand the interaction of attention and cognitive load that is crucial to the performance of many everyday tasks and our conscious experience. It can also help improve the detection and assessment of human activity in various real-world scenarios. Our findings on predicting user response at the onset of tasks can have significant ramifications for user interface design and interaction. This includes but is not limited to averting user degradation in military applications such as missile drone guidance, user performance with micro-surgical robotics in medical scenarios, driving assistance, or in early educational contexts, among others. Our method can improve user-testing effectiveness when applied in market research or product design. The contribution of this work can lend designers and multi-disciplinary researchers more insight into predicting users' response from earlier stages of their relevant work tasks to better inform their design choices, methods and analysis.

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