Effects of Counting Seconds in the Mind while Reading

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ABSTRACT

In cognitive psychology, attention and distraction are two phenomena that do not always harmonize well with each other. Nowadays, with the vast amount of information potentially available to us, it has become challenging to avoid being distracted and remain attentive when involved in an activity. In this work, we describe a way to control distraction during reading activities. We start with an experiment to measure participants' reading behaviors, which led to further analysis of how distractions affect readers' capabilities. We follow this with an attempt to statistically model the cognitive states using the data from our experiment. Finally, we propose two cognitive state recognition approaches (interest and distraction) in with and without distractor conditions.

CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile computing theory, concepts and paradigms.*

KEYWORDS

Eye tracking, reading activity, experimental design in the wild.

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1 INTRODUCTION

Attention can be diverted due to a wide variety of stimuli, which could often be not related to the performed tasks [5]. Many people have frustrating experiences of being accidentally sidetracked from their intended concentration, and such distraction may be quite disruptive in a number of daily life situations [12, 14]. During more perceptually demanding activities, which fully exhaust perceptual capacity and therefore decrease or prohibit distractor processing, distraction can be lessened or completely avoided. On the other hand, tasks that inflict a low level of perceptual load leave free capacity for processing, potentially distracting non-task inputs [5].

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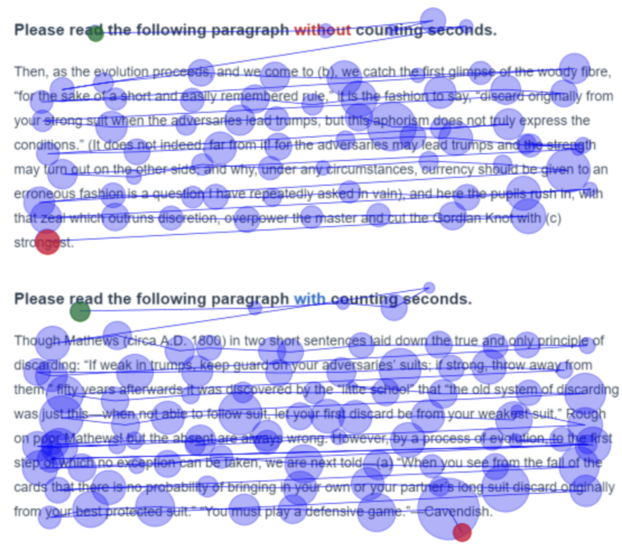
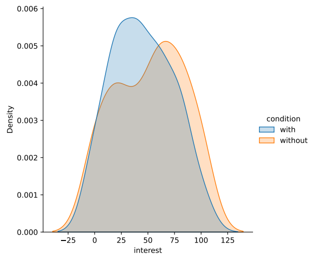


Figure 1: Scan-paths of gaze data while reading (top) and reading with counting seconds in the mind (bottom).

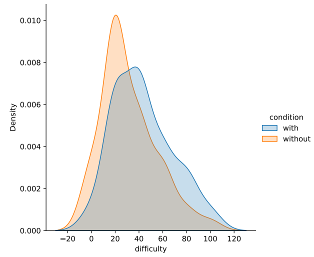
While some papers suggest that habitual media multitasking is linked to increased sensitivity to distractions [11], others show that habitual media multitaskers perform poorly across a variety of cognitive tasks independent of the presence of distractions [13]. On the basis of these importance, several researchers have been investigated tool-assisted attention sensing and interventions [6–8]

Wiradhany et al. used experience-sampling probes to see if internal distraction had an impact on performance during change-detection task [15]. A large scale study found that media multitasking is neither linked to greater sensitivity to external distraction nor lower performance owing to the occurrence of internal distraction [1]. Brishtel et al. explored how text semantics and music affect the frequency and kind of mind-wandering and observed that mind-wandering was most frequent in texts for which readers had high expertise and when combined with sad music [3]. The correlation between media multitasking and cognitive task performance suggests that media multitasking is linked to poor overall task performance, which might be due to participants being distracted by something unrelated to the task [13].

A variety of factors might generate distractions, including a lack of interest in the primary task, mind wandering, information overload, etc. In this study, we have introduced a method to induce distraction in users manually by asking them to count seconds in mind while performing a task and tried to resolve a significant constraint of collecting ground-truth labels in interval-based studies, as it requires collecting feedback from participants in each activity.

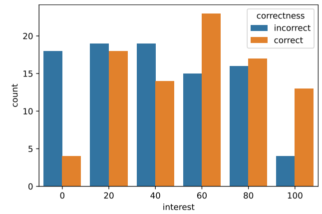


(a) Interest Levels

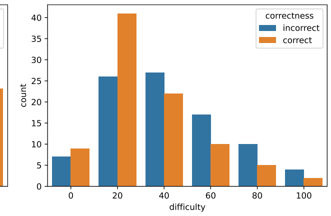


(b) Difficulty Levels

Figure 2: Distributions of the subjective evaluation about texts by all participants while with or without counting.



(a) Interest vs Correctness



(b) Difficulty vs Correctness

Figure 3: Relations of objective comprehension (the number of correct answers) and the counting detractor aggregated based on difficulty and interest levels.

One of the theoritical reasons to think that counting seconds could be conducive to distraction is that internally forced articulated speech of changing states could be representative on the one hand of the inner discourse tied to a person's stream of thoughts and on the other hand of the disruptive effects of external irrelevant sounds that occupy the phonological loop in a rehearsal task. In this regard, our distractor requires resources for the processes of generating the phonological speech and at the same time maintain the executive functions of the working memory.

A pilot study was conducted by designing a new distractor where the participants were asked to count seconds in mind while reading. The main objective behind this technique was to see how this distraction might influence the participant's ability to pay attention. We used a remote eye tracker (Tobii 4C) to record precise eye movements on the documents, nonetheless, our findings can be utilized in studies using both remote and head-worn eye trackers (e.g., Tobii Pro Glasses, HTC Vive Pro Eye, Microsoft HoloLens2).

In summary, the contributions of our work are:

- A distractor based on counting seconds in mind while reading that is designed for collecting the ground truth semiautomatically, thus reducing the limitation of constantly getting feedback from the participant such as in-the-wild studies.
- Distraction and interest detection methods that are evaluated with our gaze dataset including 10 readers were involved.

2 EXPERIMENT AND DISTRACTOR DESIGN

We collected eye movements in a study where 10 participants were asked to read a series of documents on a PC screen. They read six news articles. Each article consists of three paragraphs and we prepared a software which displays one single paragraph according to a programable order. We shuffled the order of articles for each participant but we kept the paragraph order as it is. The background images in Figure 1 show examples. Participants read each paragraph with or without counting seconds in their minds depending on the direction. The condition order was fixed to alternate (i.e., with, without, with, without). In summary, we collected reading behaviors on 18 paragraphs including nine with distractor conditions and nine without distractor condition for each participant.

To ensure they were reading attentively, each paragraph was followed by a Yes/No comprehension question about the paragraph. In addition, subjective feedback for each paragraph (interest and difficulty levels as scores of 0 - 100 in six-point scale) were collected. Participants also reported the time taken to finish reading one paragraph in the with-distractor condition.

Reading behaviors were recorded with Tobii 4C remote eye tracker with an academic license. We collected the measures: timestamp, x and y locations of the eye gaze, and pupil diameters. The following sections describe a deeper introspection and analysis of the recorded data.

3 DESCRIPTIVE ANALYSIS

In this section, we describe a deeper analysis on the recorded data. Our intention was to gain considerable insights and correlations that in turn might help us to better formulate the problem statement.

Counting distractor and eye movements: Figure 1 shows two examples of scan-paths including without-distractor condition (top) and with-distractor condition (bottom). Each circle represents a fixation, including its fixation duration as the radius. The two plots are outputs from one reader, different paragraphs in one same article. They depict that our counting distractor increases the fixation duration and the frequency of losing the location of reading, in particular during line-break.

Overall distribution of the difficulty and interest levels: Figure 2 depicts the distributions of the interest and difficulty levels. We considered how the data is distributed in both cases - one where distraction is enforced and and another when it is not. We observed following two findings. For interest levels, the distribution were slightly shifted towards higher levels when the distraction was not enforced upon, hinting that the participants were more interested when they were not distracted. For difficulty levels, the distribution were slightly shifted towards higher levels when the distraction was enforced upon, hinting that participants found the text to be difficult when they were distracted.

Interest/Difficulty levels with correctness: Figures 3 shows how difficulty and interest levels relate to correctness. The observations follow the intuitive explanation that the correctness decreases with increased difficulty levels.

Interest/Difficulty levels with distraction: As expected, Figure 4 shows that the interest and difficulty levels of texts are negatively correlated. Interestingly, we found that the difficulty levels are relatively higher when the distraction was enforced. In addition, our counting distractor increased the subjective difficulty of texts in all interest levels.

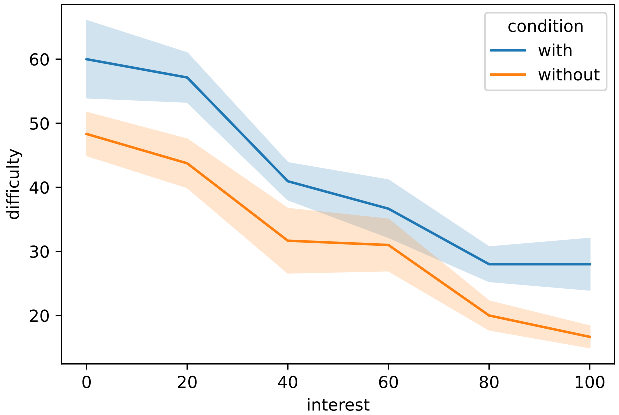


Figure 4: Relation with Distraction

Table 1: The list of features

No.	Name
1	Fixation count
2, 3	Fixation duration {mean, std}
4, 5	Forward saccade length {mean, std}
6, 7	Forward saccade angle {mean, std}
8, 9	Backward saccade length {mean, std}
10, 11	Backward saccade angle {mean, std}
12, 13	Fixation duration {mean, std}
14, 15	Line breaks lengths {mean, std}
16, 17	Line breaks angles {mean, std}
18, 19	Pupil diameter {mean, std}

4 DISTRACTION AND INTEREST DETECTION

In this section, we introduce our distraction and detection approach using eye movements. On visualizing the raw gaze data from the participants over the documents, we observed that gaze data of one participant were often missing because of a calibration problem. Therefore, we exclude the participant (i.e., we utilize gaze data of 9 participants out of 10) for further machine-learning tasks.

4.1 Features Extraction

We calculate features related to fixation and saccades. Fixation and saccade correspond to two main features in gaze data analysis. Fixation refers to the collection of raw gazes that are relatively stationary and are focused onto a single location. This is the point when our visual system takes in the detailed information about what is being looked at. Saccades are eye movements in between fixations where we shift our focus from one point to another.

We incorporate a sliding window mechanism to increase the number of training samples and applied a fixation detection [4]. Then we construct the features as shown in Table 1. Saccades can be divided into: forward, backward, and line break. We define forward saccades as saccades that represent normal reading behavior in the forward direction. Backward saccades are the moments when the reader revisits a line of text. This can be filtered out from the rest of the saccades when the difference in gaze in the horizontal direction is negative. Line breaks are the instances where the reader shifts eyes from the current line to the next line.

4.2 Model Training

We evaluate the feasibility of the models - Support Vector Machine (SVM), Random Forest (RF), Multi-Layer Perceptron (MLP). With insights from the empirical analysis discussed in the previous sections, in this section, we discuss leveraging a statistical classifier for modelling the cognitive states of the reader. In particular, we estimate the level of distraction a reader faces while reading the document. We also intend to estimate if at a given point of time, whether the reader is interested in the text. We model the problem as a binary classification with the features discussed above and the binary labels being *distracted* and *interest*. As part of the ground-truth data, for the *distracted* label, we mapped the features corresponding to the document where the participants were asked to count the seconds to a label of one (i.e., distracted) and zero otherwise. For the label *interest* we converted the interest levels recorded from the participants (as a rating scale from 0 - 100) into binary labels. As seen from the distribution of interest levels from Figure 2, the distributions with and without condition are not exactly aligned and hence we selected the score of 40 to be the threshold for binarizing the ground-truth.

4.3 Validation Method

We calculate the precision, recall, F1-score, and accuracy because it is important to decide whether we need to improve precision (decrease false positives) or recall (decrease false negatives). If we design a personalized content creation system based on the reader's distraction levels, it makes sense to have low false positives in order not to overwhelm the reader by unnecessarily modifying the content. Hence, based on the use case, we can appropriately decide on which model and evaluation metrics to consider. Each model was validated using following three techniques.

User-independent (leave-one-participant-out): Here, we trained the model with the features for all but one participant, while using the remaining participant's gaze data as validation set. This helped us analyze how well a model generalizes to new participants.

User-dependent (leave-one-document-out for one participant): In this type, for each participant, the model was trained with the gaze data of all but one document as the train set and the gaze data of the remaining document as the validation set. This enabled the model to effectively model the gaze pattern for each reader and therefore predict when the reader is distracted. Here, the performance of the model for each document and in-turn for each participant was recorder and averaged.

Document-independent (leave-one-document-out for all participants): Here, we define document in this paper as one paragraph. We use the features of all but one document as our training set and gaze data on the remaining one document as our test set. Here, the performance of the model for each document was recorded and averaged in our analysis.

Table 2: Performance report of multiple classifiers (Support Vector Machine, Random Forest, and Multi-Layer Perceptron)

Classifier	Validation method	Distraction				Interest			
		Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-score	Accuracy
SVM	User-independent	0.550	0.482	0.514	0.508	0.648	0.628	0.637	0.521
	User-dependent	**0.605**	0.560	**0.582**	**0.566**	0.704	0.727	0.715	**0.631**
	Document-independent	**0.662**	0.555	0.600	**0.582**	**0.672**	0.598	0.632	0.535
RF	User-independent	**0.565**	**0.613**	**0.588**	**0.538**	**0.672**	**0.898**	**0.769**	**0.638**
	User-dependent	0.589	**0.562**	0.575	0.553	0.697	**0.750**	**0.723**	0.614
	Document-independent	0.585	0.569	0.572	0.518	0.643	0.777	**0.703**	**0.562**
MLP	User-independent	0.551	0.558	0.554	0.517	0.671	0.781	0.722	0.590
	User-dependent	0.561	0.535	0.548	0.524	**0.707**	0.721	0.714	0.612
	Document-independent	0.641	**0.611**	**0.621**	0.580	0.659	**0.707**	0.681	0.558

4.4 Results

Table 2 summarizes the results of our experiment. The highest score among three classifier for each validation method is highlighted as a bold font. We found that a Random Forest Classifier performed better compared to others, in particular, in user-independent cross-validation (F1-Score 0.588 for detecting distraction and 0.769 for detecting interest).

We further infer from the table that the performance of the models are relatively stable across for all hold-out documents. The leave-one-document-out technique for each participant also seems to have higher values implying that having a model learn patterns exclusively for each individual for cognitive state analysis might be helpful while designing highly personalized systems.

5 DISCUSSION

The eye tracking study employed a distractor as participants read documents and is based on counting seconds in mind while reading. This approach streamlines the ground truth gathering procedure, which often involves collecting self-report surveys or questionnaires from participants, which might have an impact on the study.

The participants were required to engage in distraction in order to see how it affected their cognitive capacities while performing a reading task. The interest and difficulty levels of the documents were compared with and without distraction. It was found that when the participant was not distracted, the interest level was higher indicating that reading without being distracted mitigated the influence of text difficulty and increased interest level. Across various studies, the prevalence of a distractor has been shown to have a direct impact on the functioning of cognitive processes. Tasks in which users were asked to engage in task-unrelated thoughts often lead to a divided attentional state [2], hence cause various negative consequences such as difficulties sustaining attention, relapsed mood [9], and remarkably obstructing memory encoding.

Similarly, when the participants were distracted the difficulty scores were greater which in turn negatively affected their correctness score on the associated questions. This finding supports the executive resource hypothesis that a distracting agent will increase the task difficulty as the availability of competing attentional resources diminishes. In the same regard, Navalpakkam and colleagues showed that under high levels of distraction [10], participants needed to put more effort into the text, performed more fixations, and frequently revisited previously read content.

The performance of the machine learning models and the Multi-Layer Perceptron were relatively similar. For distraction detection, the MLP with Document-independent approach had better precision, recall, and F1-score while the Random Forest model with User-independent approach had better accuracy, F1-score, and recall for interest detection from Table 2. One of the major limitation with this study was the limited number of data samples. To increase the number of data samples, a sliding window algorithm was used but still the number were not big enough for better performance evaluation. When comparing the evaluation metrics for both distraction and interest detection, it was observed that the interest detection results were more promising than distraction detection.

Results using user-dependent and user-independent validation techniques showed that the accuracy was slightly higher for all the models using user-dependent validation technique. These findings may not be sufficient enough to conclude that differentiating attention from distraction is highly user-dependent.

6 CONCLUSION AND FUTURE WORK

In this study, we introduced an approach to capture and model distraction while reading. We conducted an experiment where we asked participants to count seconds in their mind while undergoing a reading assignment to establish a semi-automated approach for gathering ground truth. The correlation between the participants' interest and difficulty ratings, when they were distracted and when they were not distracted was analyzed. Random forest, SVM, and MLP models were implemented using different cross-validation methods to predict the distraction and interest of the participants.

As part of the future work, we would like to utilize more powerful ensemble models, deep learning-based CNNs, and temporal models like LSTMs to effectively model the eye gaze data. A prior knowledge of whether the reader is distracted or not might provide additional relevant information during the estimation of interest and difficulty levels. We explore extending the current implementation with additional functionalities like adapting the content of the text the reader is reading based on his/her cognitive states.

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