

# Automatic Gaze-Based Detection of Mind Wandering during Reading

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## ABSTRACT

We present a fully-automated person-independent approach to track mind wandering by monitoring eye gaze during reading. We tracked eye gaze of 84 students who engaged in an approximately 30-minute self-paced reading task on research methods. Mind wandering reports were collected by auditorily probing students in-between and after reading certain pages. Supervised classifiers trained on global and local features extracted from students’ gaze fixations 3, 5, 10, and 15 seconds before each probe were used to predict mind wandering with a leave-several-subjects-out cross validation procedure. The most accurate model tracked both global and local eye gaze in a 5-second window before a probe and yielded a kappa (accuracy after correcting for chance) of 0.23 on a downsampled corpus containing 50% yes and 50% no responses to probes. Implications of our findings for adaptive interventions that restore attention when mind wandering is detected are discussed.

## Keywords

Mind wandering, eye gaze, affective computing, affect detection

## 1. INTRODUCTION

Mind wandering (or zoning out) is a phenomenon in which attention drifts away from the primary task to task-unrelated thoughts [1]. It is critically important to learning because active comprehension of information involves extracting meaning from external sources of information (e.g., text, audio, image) and aligning this information with existing mental models that are ultimately consolidated into long-term memory structures. Mind wandering signals a breakdown in this coupling of external information and internal representations. Hence, it is no surprise that mind wandering has disastrous effects on learning and comprehension because it negatively impacts a learner’s ability to attend to external events, to encode information into memory, and to comprehend learning materials [2, 3]. Therefore, there is a crucial need for interventions to track and restore attention when mind wandering is detected.

A system that responds to mind wandering must first detect when minds wander. In line with this, Drummond and Litman [4] attempted to identify episodes of “zoning out” while students were engaged in a spoken dialog with an intelligent tutoring system (ITS). Students were periodically interrupted to complete a short survey to indicate the extent to which they were focusing on the task (low zoning out) or on other thoughts (high zoning out). J48 decision trees trained on acoustic-prosodic features extracted from the students’ utterances yielded 64% accuracy in discriminating high vs. low zone-outs. This study was pioneering in that it represents the first attempt to automatically detect zone-

outs. However, it suffers from two notable limitations. First, the study used a leave-one-instance-out cross-validation method where training and testing sets were not independent; therefore it is unclear if the model generalizes to new students. Second, the model is only applicable to spoken tutorial sessions instead of more general learning tasks.

Taking a somewhat different approach, we report initial results of a study that uses eye gaze data to develop *student-independent* predictive models of mind wandering during reading. Our emphasis on reading is motivated by the fact that reading is perhaps the most ubiquitous learning activity. Our focus on eye gaze to track mind wandering is motivated by decades of scientific evidence in support of an *eye-mind* link, which posits that there is a tight coupling between external information (words on the screen) and eye movements [5]. For example, previous research has found that individuals are less likely to fixate, re-fixate, and look backward through previously read text [6] and blink more frequently [7] when mind wandering compared to normal reading. The present study builds on these findings by developing the first gaze-based mind wandering detector.

## 2. METHOD

### 2.1 Labeled Data Collection

A Tobii T60 eye tracker was used to record gaze patterns of 84 students while they read four texts on research methods (e.g., random assignment, experimental bias) for approximately 30 minutes. Students read the texts on a page-by-page basis (roughly 144 words per page) and used the space bar to navigate forward. Mind wandering was measured via auditory probes, which is the standard and validated method for collecting online mind wandering reports [1]. When a student’s gaze fixated on previously determined “probe words”, which were pseudo-randomly inserted in the texts, the system played an auditory cue (i.e., a beep) to prompt the student to indicate whether or not he or she was mind wandering by pressing keys marked “Yes” and “No.” These probes are referred to as *in-between page probes*. In addition, *end of page probes* were triggered when students pressed the space bar to advance to the next page. There were approximately 10 probes per text and reports of mind wandering were obtained for 35% of the probes, which is comparable to rates obtained in previous studies on reading [2].

### 2.2 Feature Engineering

Gaze fixations were estimated from the raw gaze data using OGAMA, an open source gaze analyzer. The series of gaze fixations were segmented into windows of varying length (3 secs, 5 secs, 10 secs and 15 secs), each culminating with a mind wandering probe. The windows ended immediately before the

probe was triggered in order to avoid confounds associated with motor activities in preparation for the key press. Furthermore, windows with less than five fixations were eliminated because these windows do not contain sufficient data to meaningfully compute gaze features.

Two sets of gaze features were extracted from gaze fixations in each window. *Global features* were independent of the actual words being read and consisted of fixation frequency, fixation durations, variability in fixation durations, saccade lengths, etc. *Local features* were sensitive to the words being read and included relationships between word length and fixation duration, number of words skipped, length of first pass fixations, etc. There were 17 global features, 12 local features, and 25 global-local features (two features were eliminated due to multicollinearity).

### 2.3 Supervised Classification

A host of 33 supervised machine learning algorithms from Weka [8] were used to build models to discriminate mind wandering (responding “yes” to the probe) from mindful reading (responding “no” to the probe). The 33 classifiers (with default parameters as specified in Weka) were run on the 3 feature types (global, local, global + local), 4 window sizes (3, 5, 10, and 15 seconds before probes), and on 4 configurations of the data (raw data, raw data with outliers removed, downsampled data with 50% “yes” and “no” responses, and downsampled data with outliers removed), yielding 1584 models in all. A leave-several-subjects-out validation method was employed in which data from a random 66% of the *subjects* were selected for the training set and the remaining 34% of subjects were used in the test set. This process was repeated for 25 iterations and classification performance was averaged across these iterations. The kappa metric was used to quantify classifier performance because it controls for random guessing.

### 3. RESULTS

The best results were obtained from the downsampled corpus without outlier removal. Mean kappas and standard deviations (across 25 iterations and shown in parentheses) for the best performing models for each feature type are shown in Table 1.

**Table 1. Results for best performing models**

Features	Kappa	RR.	Win	N	Classifier
Global (G)	.14	56.2	5	37	Multiboost
	(.10)	(5.55)		4	Adaboost
Local (L)	.08	53.7	15	40	Naïve Bayes
	(.06)	(4.21)		2	Updatable
<b>Global + Local</b>	<b>.23</b>	60.0	5	37	Locally-weighted learning
	<b>(.08)</b>	(6.35)		4	

*Note.* Standard deviation is in parentheses. RR. = recognition rate. Win = window size. N = number of instances.

The results support several conclusions on the feasibility of automatic detection of mind wandering by tracking eye gaze. First, although classification accuracies are moderate, the best performing models (Global + Local) detected mind wandering at rates significantly greater than chance. Second, the training and testing data were completely independent, so we have some confidence that the models generalize to new students. Third, the global models yielded higher accuracies than the local models. Fourth, a combination of global-local features resulted in a substantial improvement over the individual feature sets. Finally,

gaze tracking over shorter window sizes (5 secs) was more effective than longer windows.

### 4. GENERAL DISCUSSION

Mind wandering is a ubiquitous phenomenon that has disastrous consequences for learning because it a quintessential signal of waning attention. We present a proof-of-concept of the possibility of automated tracking mind wandering during reading. Although we had some success in developing person-independent models to detect mind wandering, the accuracy of our models was moderate. We are currently in the process of refining our models by both increasing the size of the training data while simultaneously considering a larger feature space and more sophisticated classifiers. When coupled with the falling cost of eye trackers and the potential use of web-cams for low-cost gaze tracking, we expect that these improvements will yield sufficiently robust and scalable detectors of mind wandering. In turn, these detectors can be used to trigger interventions to restore engagement by reorienting attention to the task at hand.

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