# Analyzing Eye Gaze of Users with Learning Disability

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## ABSTRACT
This paper investigates eye gaze movements of children with different reading abilities due to learning disability. We analyzed eye gaze fixations using cluster analysis and velocity-based fixation classification algorithms. We used a non-invasive, screen mounted, low-cost eye tracker to collect data from 30 participants including students with learning disabilities. We analyzed raw gaze points, fixations and saccades, and noted that the density of gaze points around fixation. Total number of fixations and regressions (backward gaze movement) were statistically significantly correlated to the reading ability of students. We concluded that by analyzing different eye movements for a representative reading task, we can detect early signs of learning disabilities such as dyslexia.

## CCS Concepts
**• Human-centered computing→Human computer interaction (HCI)Information systems→Empirical studies in HCI**

## Keywords
Eye gaze tracking; Dyslexia; Fixation; Regression; Soft clustering.

## 1. INTRODUCTION
This paper investigates eye gaze movements of children with different reading abilities using a commercial eye gaze tracker. Eye tracking is the process of measuring either the point of gaze or the motion of an eye relative to the head. It gives an in-depth understanding of ongoing cognitive processes such as reading [14]. Learning Disability (LD) is an umbrella term that includes difficulty in reading (dyslexia), mathematics (dyscalculia) and writing (dysgraphia). At a press conference during the release of DALI in October 2015, the Minister for Science & Technology [11] included the fact that, out of students who suffered from LD, 70-80% have deficits in reading. Five to Fifteen percent of children in India are having dyslexia. Early identification of these disabilities can help in significant improvement of such children [20].

Dyslexia is the most common type of LD. People with Dyslexia have difficulty in learning to read or interpret words, letters, and other symbols. This does not affect general intelligence, but they are perceived to be dull or lazy. Children with dyslexia often spend many years struggling in school before receiving appropriate professional support. Efficient screening methods that can be easily deployed in school settings are important instruments to counter this situation and facilitate earlier support for those at risk of long-term reading difficulties. Eye movements of dyslexic readers are already found to be different from those of typical readers [3]. By tracking eye gaze movements during reading, we can follow the behavior of reading and obtain objective measurements of this process. Importantly, this mode of measurement requires no overt response, extraneous to the reading process itself and thus makes it feasible to assess reading performance without placing additional task demands on the subject. We analyzed spatial distribution of gaze points using soft clustering algorithm. We also identified the characteristic features of a participant using velocity-based fixation classification algorithm. Then, we performed correlation testing between the identified parameters and subjective rating of reading skill which were given by a trained instructor. These parameters can be used further to develop an automatic system to detect early signs of learning disability using non-invasive commercial off the shelf low-cost eye gaze tracker. Main contributions of this paper are:

- Analyzing spatial distribution of raw gaze points through cluster analysis and finding relation between number of fixation clusters and reading ability.
- Identifying metrics for poor reading and correlating the subjective rating with the identified metrics in context of learning disability.

## 2. LITREATURE REVEIEW
Multiple branches of science such as psychology, cognitive neuroscience have contributed to detection and diagnosis of dyslexia [3]. In this paper, we only focus on how eye tracking measures have been studied in relationship with dyslexia. Dyslexia [15] can be defined as a processing difference, often characterized by difficulties in literacy acquisition affecting reading, writing, and spelling. It can also have an impact on cognitive processes such as memory, speed of processing, time management, coordination and automaticity. There may be visual and/or phonological difficulties and there are usually discrepancies in educational performances.

Researchers already found that font types have an impact on the readability of people with dyslexia. Good fonts for people with dyslexia are Helvetica, Courier, Arial, Verdana, and CMU, taking into consideration both, reading performance and subjective preferences [16]. Font size has a significant effect on the readability and the ability to understand text, while line spacing does not [18]. 18-point font size was recommended when designing web text for readers with dyslexia. Kamala et al. [8] noted that as time passes by, dyslexia grows in many ways and may be difficult to identify. It should be an effort by teachers, parent's psychiatrists to continuously observe the child's performance in every aspect. Benfatto et al. [3] reported that, we


*ICGSP '19*, June 1–3, 2019, Hong Kong, Hong Kong

ACM ISBN 978-1-4503-7146-9/19/06…$15.00
https://doi.org/10.1145/3338472.3338481

may not get reliable results for school children considering oral or written tests to identify dyslexia. Rather, eye tracking is a natural and silent way of capturing the responses as it does not rely on any overt responses.

Eye movements are any shift of position of the eye in its orbit. There are different kinds of eye movements like fixations, saccades, pupil dilation, and scan paths [2]. Eye movement coordinates provide a literal account of the cognitive processes [14]. Eye gaze has already been used for modelling visual perception including people with visual and cognitive impairment [4]. They prove to be highly predictive of individual reading ability and that they can be an efficient means to identify children at risk of long-term reading difficulties [3]. Eye movement characteristics during reading reflect the difficulty that children have understanding written text [13]. Readers of English language texts are more likely to prefer the whole-word approach [23]. Tool such as "Dyslexia Explorer" [1] is designed to screen for dyslexia by examining visual attention in reading Arabic script. The tool analyses the eye gaze coordinates and provides interactive charts with thresholds to explore the reading analysis' results for distinguishing between readers with and without dyslexia. Rapid Assessment of Difficulties and Abnormalities in Reading (RADAR) [21] is another test that helps to analyze children with reading disorders like dyslexia in a group of school-age children ranging from 8.5 to 12.5 years. Several researches have been conducted using artificial neural networks, regression-based procedures and other machine learning methods to identify dyslexia. Lustig [9] investigated use of machine learning methods to analyze eye movement patterns for dyslexia classification with 83% accuracy [7]. Rello and Ballesteros [17] used a similar approach based on SVM binary classifier with the eye tracking data and they were able to achieve 80.18% accuracy.

# 3. PROPOSED APPROACH

This study investigates early signs of dyslexia in participants aged between 8-10 years by analyzing their reading pattern using eye tracking. We developed a software (Figure 1) which displays text and records gaze data of the participant using eye tracking.

**Participants:** We collected data from 30 participants. These participants were grouped into two, based on their age. Group 1 users were aged between 21-30 years and Group 2 users were aged between 8-10 years. Group 2 users were asked to read two paragraphs of grade appropriate text on the screen. Group 1 users were also asked to read the same text. All participants in Group 2 had equal years of learning with varying reading abilities. In total, we collected data from about 30 participants –10 from Group 1 (02 females and 08 male) and 20 from Group 2 (11 females and 09 male).

**Design:** The GUI (Graphical User Interface) consisted of three sections as shown in figure (Figure 1). On the top left portion of the UI, the user can import a text file of his/her choice. The text is displayed in the middle section of the screen to facilitate easy reading. We used English text with Open Dyslexic-Regular font type and 18-point font size. The bottom right portion of the UI has the 'Next' button using which the user can navigate to the next screen for the second paragraph in the text file.

**Material:** A Lenovo Yoga Laptop with 14'' display running on Windows 10 operating system was used to conduct the experiment. Gaze data was recorded using a low-cost eye gaze tracker (Tobii EyeX tracker, frequency of 60 Hz) with bespoke software written using the Tobii SDK.

**Procedure:** Initially, all participants were asked to undertake a triangular calibration routine using the Tobii software. They were then instructed to read aloud the text displayed as two separate paragraphs one after the other. The participants were asked to read the sentences at their own pace. We recorded the participant's gaze points along with time stamps.

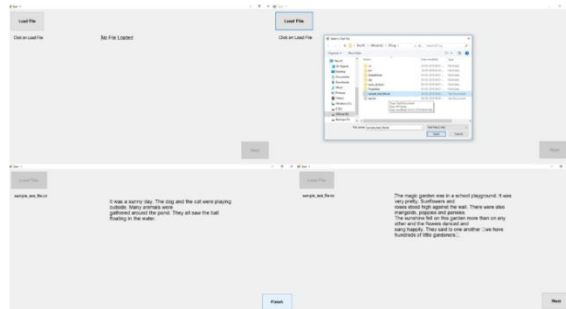

**Figure 1. GUI of software: no file loaded; load text file**

**Analysis:** Eye movements, in general, can be categorized into two: fixations and saccades. Fixations are a general group of eye movements that function to examine a visual scene in one area. Saccades are another general group of eye movement that shifts a gaze fixation location from one place to another. In everyday life, humans alternate between a saccade and a fixation repeatedly. Eye movements of readers with dyslexia are different from regular readers [6]. People with dyslexia make more and longer fixations, shorter saccades, and more regressions than readers without dyslexia [10,14]. We asked a trained instructor to rate the participants (Subjective Rating) between 0 to 5 based on their reading ability. We analyzed the recorded gaze values using the following two approaches.

1. In analysis 1, we investigated the spatial distribution of raw gaze points through cluster analysis for both groups of users.
2. In analysis 2, we extracted fixations from raw gaze data using a velocity-based fixation algorithm and analyzed the number and duration of fixation points and directions of saccades. We undertook this analysis for only Group 2 of users.

**Cluster Based Analysis:** In this analysis, we investigated the spatial distribution of gaze points through cluster analysis. The whole analysis was on raw eye gaze points recorded by the eye tracker. Instead of assuming a fixed number of clusters, we aimed at automating the process of generating an optimum number of clusters for any given data using Expectation Maximization algorithm. We used Xie-Beni (XB) index cluster validation metric to evaluate the degree of goodness for the generated clusters. We performed this analysis in order to identify distribution of gaze points and also the size of each cluster for each user.

**Expectation Maximization (EM) Algorithm:** Expectation maximization algorithm uses an iterative rarefaction technique and works best as a clustering tool. The EM algorithm is a general method of finding the maximum-likelihood estimate of the parameters of the distribution from a given dataset when the data is incomplete or has missing values. The main application of EM Algorithm is when the data contains missing values, due to issues pertaining to the limitations of the process of observation. The EM method is a two-step iterative algorithm. The first step called the Expectation step, or the E-step involves estimating the probability distributions of the clusters given the data. The second step, called the Maximization step or the M-step, involves finding the model parameters that maximize the likelihood of the solution. The algorithm terminates once the threshold is reached.

**Cluster Validation Metric:** Validation metric is used to check how good clustering is performed by generating crisp clusters without any overlapping of cluster data values. The validation metric is categorized into two classes namely, • Internal Validation: Based on the information innate to the data only. • External Validation: Based on prior knowledge about data. Internal validation is used to measure the extent to which cluster labels match externally. Examples include BIC Index, Dunn index and so on. External validation indices require a priori knowledge of data set information, but it is hard to say if they can be used in real problems. Examples include F-measure, XB index, Entropy. In our case study, we have used XB index as a validation metric. We have thus implemented the two soft clustering algorithm (EM) with XB index cluster validation metric. To evaluate the cluster results obtained from our algorithm, we developed a software which allows the user to manually plot points and form clusters of their interest. The coordinates of these data points were logged respectively. These coordinates were then fed to EM algorithm.

From the user study, we logged raw gaze values of each participant while they read each paragraph. The data was filtered using a technique called boundary box. Here, we drew a boundary of interest (Figure 2) around the text displayed for the participant to read. We then considered the raw gaze values that belong to the boundary box and eliminated the rest. This filtered data was then fed to EM algorithm through XB index validation metric. We did so to focus and extract gaze values in the text area alone rather than using the entire gaze data. Output of EM algorithm was optimum number of clusters, cluster centers and cluster size of each of the optimum number of clusters generated. Steps for analysis 1 is mentioned below:


**Figure 2. Coordinates for identifying boundary**

**Results:** The study was executed in a sequential flow.

- Gaze data values with timestamps from the user study were recorded.
- Data filtering using boundary box technique was performed.
- Filtered data were then clustered using Expectation Maximization soft clustering algorithm.
- Optimum number of clusters, cluster centers and sizes of each cluster were tabulated.

We calculated the total time taken by participants of both groups to read the entire text displayed on the screen. It was found that the time taken by both groups of users showed considerable variation among them (Figure 3). Among the Group 2 users, 4 out of 20 participants took as much as twice the time as compared to their peers. An independent samples t-test was conducted to compare time taken by Group 1 and Group 2 users. There was a significant difference between the two groups of users; ( $t(29)=3.74$, $p<0.05$). These results suggest that Group 2 users took more time (2.1 minutes) to fixate attention and read when compared to Group 1 users (0.37 minutes).

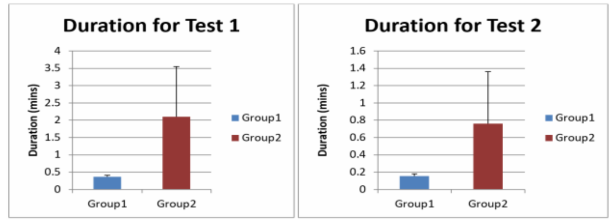


**Figure 3. Total time taken to read each of the paragraphs by both groups of users**

Using EM algorithm, we generated optimum number of clusters of gaze points for each participant. This was done to find out the number of areas the participant fixates for a longer duration. Upon analysis, we found that there was no significant difference (Figure 4) between two user groups (Optimum number of clusters is 3 for both groups) Then, we calculated the size of each cluster (number of points belonging to each cluster) in the optimum number of clusters and calculated the median cluster centers (Figure 5). A Mann-Whitney U test on median cluster size between the groups found that the median cluster size was significantly different between Group 1(381.25) and Group 2(1490.14); $U = 14$, $z = 3.82432$, $p < 0.05$, $r=0.69$, which indicates that Group 2 users take more time to fixate at a position on screen while reading when compared to Group 1 users.

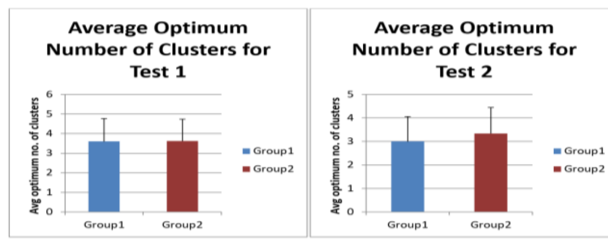


**Figure 4. Optimum number of clusters for both groups of users**

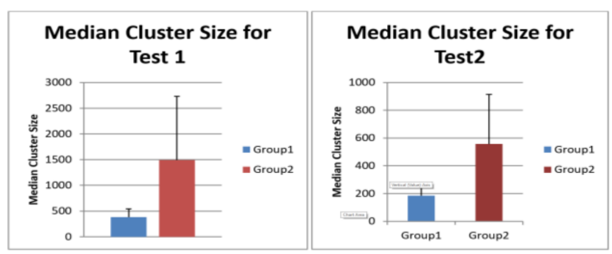


**Figure 5. Median cluster size for both groups of users**

**Velocity-Based Fixation Analysis:** To further investigate the differences in reading abilities among Group 2 users, we extracted eye movements like fixations and saccades from raw gaze data. To classify eye movements into fixation and saccade, we implemented an algorithm called velocity-based fixation analysis. Then, we correlated the following parameters with range of reading abilities of users:

- Average number of fixations for each participant
- Percentage of backward directed eye movement (regression)
- Subjective rating (Likert scale from 0 to 5) based on participant's performance

The experiment was conducted under observation of trained researchers and a school teacher. Participants were observed and given a subjective rating (on a Likert scale from 0 to 5; 0 is lowest, 5 is highest) based on their reading behavior and performance, by a trained instructor. Graph for number of participants with respect to subjective rating is shown below (Figure 6).

It can be noted that participants who had subjective rating less than 3 showed poor reading ability and as shown in Figure 6, fourteen out of twenty participants had poor reading abilities than their peers.

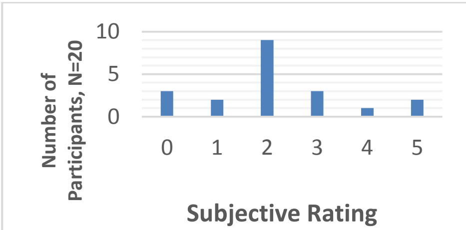


**Figure 6. Subjective rating graph for Group 2**

**Algorithm to find Fixation & Saccade:** We extracted $(x_i, y_i, t_i)$ values from the eye tracker and the missing data sequences were filled using linear interpolation. This was done to maintain consistency with uniform time interval. We incorporated the algorithm used by Mould et al. [12] to determine the difference between fixation and saccades. This algorithm was also used to implement Gaze Path, an eye tracking analysis tool [24]. Initially, we calculated velocity values by dividing the Euclidian distance between the subsequent points by the time difference. Then, local maxima were found by the immediate velocity peak value between preceding and succeeding points. Finally, we found the frequency of local maxima in a velocity-time graph. We iterated this process of finding frequency of maxima for varying threshold ranging from lowest value to the highest value of velocity. Further, we plot a graph between the frequency of local speed maxima exceeding threshold and varying speed thresholds (Figure 7). The below mentioned graph represents the threshold for one participant.

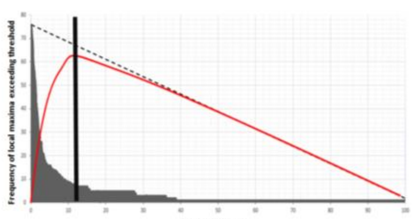


**Figure 7. Velocity threshold estimation graph**

The light grey part of the graph shows the frequency for local maxima of velocity values exceeding a variable speed threshold. The graph was then compared to a uniform null distribution [22] of local maxima exceeding the threshold marked by dotted line. The red line (gap statistic) is smoothed further with a locally weighted quadratic regression [5] until gap is maximum, and this gives the difference between these two distributions.

This maximum in the gap-statistic is marked as elbow. We used algorithm given by Satopaa [19] to find the elbow. The elbow gives the optimum velocity threshold. This velocity threshold differentiates values above this threshold as saccades and the values below are termed as fixations. It can be noted that, participants with poor reading ability have more number of fixations when compared to that of control group (Group 1) users.

**Algorithm to identify regression:** Regression is a type of saccadic eye movement. It is termed as backward movement (right to left) of the eye while reading. We identified the backward movement in gaze coordinates $(x, y)$ of the subsequent values with respect to their time difference. The time elapsed was then compared to a threshold value. If any backward movement was recorded in the succeeding gaze coordinate above a threshold time value, then it was counted to be a regression. It is significant in terms of longer regression which are related to problems with text, comprehension justifying another reason for poor reading ability.

From analysis 2, we identified and compared the fixation threshold values, average number of fixations for each participant, percentage of regression, total time taken to read with the subjective ratings and median cluster size. Considering the subjective rating in Figure 6 and the above-mentioned parameters, we noted that 14 out of 20 participants among Group 2 users showed poor reading abilities. We also noted that, none of the participants from Group 1 showed any signs of poor reading ability.

Further, we performed Pearson correlation coefficient to measure relationship between subjective rating and fixation threshold values, average number of fixations for each participant, percentage of backward directed eye movement (regression), median cluster size, total time taken to read. From this analysis, it was found that there exists a strong negative correlation between subjective rating and fixation threshold values (-0.76) average fixation for each participant (r= -0.76), regression (-0.58), median cluster size (r=-0.53), total time taken to read (r=-0.76) at $p<0.05$ as shown in table below.

**Table 1 Correlation between subjective rating and ocular parameters**

| Description | Score |
|---|---|
| Fixation threshold value | $-0.76^{**}$ |
| Avg. no. of Fixation | $-0.76^{**}$ |
| Regression | $-0.58^{**}$ |
| Median Cluster Size | $-0.53^{**}$ |
| Total time taken | $-0.76^{**}$ |

** indicates $p<0.05$

# 4. DISCUSSION

This study investigates eye gaze movements and fixations to analyze different range of reading abilities among different user groups. We designed a software to collect eye gaze points while participants undertook a text reading task. We collected data from two groups of students – one group is learning English reading for 4 years but have different abilities of reading skill while the other group is university students with no issue in reading English text. We used a qualified instructor to score students within a scale of 0 to 5 in terms of their reading abilities.

Our first analysis through soft clustering of raw gaze points did not find any significant differences in the number of optimum clusters between and within different groups of users. However, we noted that students with poor reading ability took significantly longer time to read the same length of text than others. Further analysis on the clusters showed sizes of clusters are significantly bigger for students with poor reading abilities than others. A second analysis of the group of students with varying reading abilities proposed a velocity-based fixation extraction algorithm and used it to classify raw gaze points into fixations and saccades. We noted a significant correlation between number of fixations, backward (right to left) eye gaze movements and the scores indicating students' reading abilities.

Based on the analysis, we can conclude that students with poor reading ability stay focused in one region of the text longer and make more back-and-forth gaze movements than other students with better reading abilities. By calculating the density of raw gaze or fixation points or number of regressions within an area of textual information, we should be able to indicate the reading ability of students within a short time. This analysis can subsequently be used to diagnose early sign of learning disability or dyslexia among students.

# 5. CONCLUSION

This paper investigates eye gaze movements and fixation patterns of students with different range of reading abilities. Data were collected in a school consisting of students with and without learning disabilities and from a control group of university students, who did not have any issue with reading. We analyzed spatial distribution of raw gaze points using a soft clustering algorithm and extracted fixations using a velocity profile-based algorithm. We have found that the optimum number of cluster centers did not change based on reading abilities, indicating students with or without learning disabilities fixate attention in similar number of spatial locations. However, the duration of fixation was significantly higher in students with learning disabilities. Further analysis showed that a subjective score based on reading abilities of students significantly correlated with the number and duration of fixations and regression (right-to-left) type of eye gaze movements. We propose to use these metrics to develop an automatic system to detect early signs of dyslexia.

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