EYE TRACKING GROUP PROJECT

GROUP 08

Anna Braun
University of Eastern Finland

Raffael Rizzo
University of Eastern Finland

Abolfazl Jalali
University of Eastern Finland

Chihiro Tone
University of Eastern Finland

Uzairu Abubakar
University of Eastern Finland

Aryaman Sharma
University of Eastern Finland

Shani Israelov
University of Eastern Finland

Faria Ferdowsy
University of Eastern Finland

Introduction:

The project aims to learn how to record, analyze and visualize eye-tracking data. The project is divided into two parts, the first part consists of the analysis and visualization of available data. Python was used to implement a Dispersion Threshold Fixation Detection Algorithm to detect the fixations of the test subjects from the given dataset. Two different parameters were set for the Algorithm and a deep learning model, the *U'n'Eye* model was also trained on the model. Thus, for the dataset, three different data were obtained. Comparison and analysis were done on the processed data.
The second part consists of recording data from two different eye trackers.

1 Data Recording:

The provided data was pre-recorded and was a part of a test where the subjects recognized a specific image or not.

The data is in the form of a CSV file where each line was for each test subject. Each line consists of a subject id, the decision of the test (recognized, true or not recognized, false), and a series of x and y coordinates for different gaze positions corresponding to the horizontal and vertical positions of the gaze, respectively.

The subjects were seated at 450 mm from the screen. The field of view under the test was 195 mm x 113 mm.

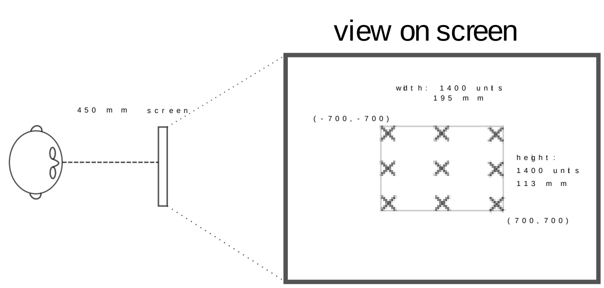

Figure 1: Test Setup [4]

2 Fixation Detection Algorithm Implementation

2.1 Chosen Algorithm

In the project work, the chosen algorithm is the Dispersion Threshold(I-DT) which uses the fact that fixation points have low velocity and a tendency to cluster together, so it identifies fixation by finding data samples that are close enough to one another for a specified minimum period. It requires two parameters to be specified: the maximum dispersion threshold (degrees) and the minimum fixation duration threshold(ms). [5]

To be a fixation, data samples constituting at least enough time to fulfill the duration threshold must be within a spatial area not exceeding the dispersion threshold. The samples fulfilling these criteria are marked as belonging to a fixation.

2.1.1 Algorithm:

The algorithm uses a moving window that spans consecutive data points, checking for potential fixation. Initially, the window spans a minimum number of points, determined by the duration threshold and sampling frequency. Then it checks the dispersion of the points in the window by calculating

$$D = [\max(x) - \min(x)] + [\max(y) - \min(y)],$$

where (x, y) represents the samples inside the window. If the dispersion is above the dispersion threshold, the window does not represent a fixation, and the window moves one point to the right. If the dispersion is below the dispersion threshold the window represents a fixation. In this case, the window is expanded (to the right) until the window's dispersion is above the threshold. The final window is registered as a fixation at the centroid of the window points with the given onset time and duration. This process continues with the window moving to the right until the end of the protocol is reached.

IDT was chosen because it produces robust and accurate identification results. The primary disadvantage of IDT is the use of two parameters that are highly interdependent. For instance, a small dispersion threshold with a large duration threshold may not result in any identified fixations. Thus, IDT requires the most careful parameter setting but provides good results for a simple algorithm.

For the project, we have implemented this algorithm with two parameters by changing the Duration Threshold.

The first implementation had a minimum duration threshold of 100ms while the second had a duration threshold of 200ms.

The results of the two runs are stored in CSV files which will be presented with the report.

1.1 Deep Learning Algorithm

For the next part of the first tax, we implemented the UnEye Deep Learning Model which is a Python 3 package, that uses PyTorch for the neural network implementation.[6]
First, the data was split and was used for training the network, and then it was used for the prediction of fixations.
The Model requires the following few inputs:
x: horizontal eye position
y: vertical eye position
labels: eye movement ground truth labels
sampfreq: sampling frequency of the data (Hz)

We trained the three algorithm runs to predict the fixations and the result of those are added in the next section.

2. Plots, Analysis and Observations

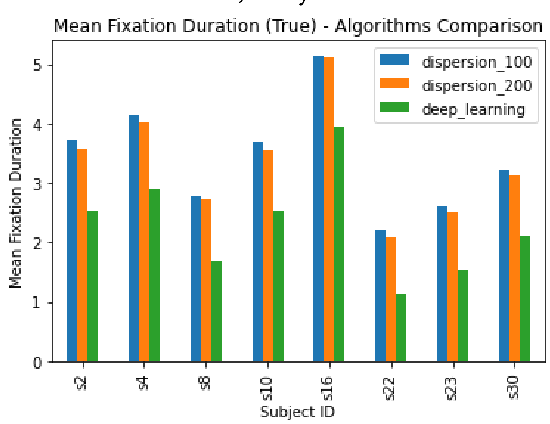

Figure 2: MFD(True)

We plot the Mean Fixed Duration for each subject and all the three algorithms.
We observe that the MFD was higher for all the subjects when the dispersion threshold was 100ms. One of the reasons behind this is that fixation points near each other were grouped together and many fixations were created as compared to the Dispersion Threshold of 200ms.
Next, we plot the MFD(False) in the same setting

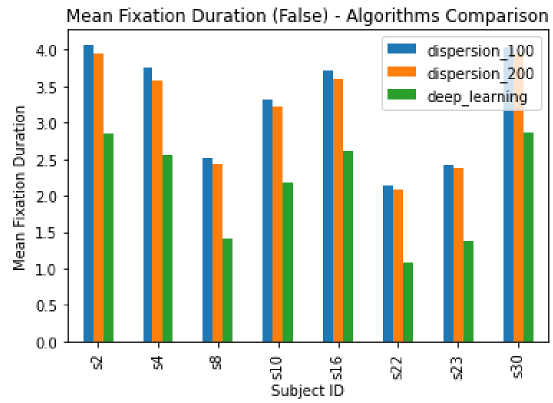

Figure 2: MFD(False)

We observed similar trend in the Mean Fixed Duration (False) as that in the previous case and that the Deep Learning Model still had the least Mean Fixation Duration.
Third, we plot the Mean Fixed Duration True for our chosen Algorithm with Dispersion Threshold of 100ms

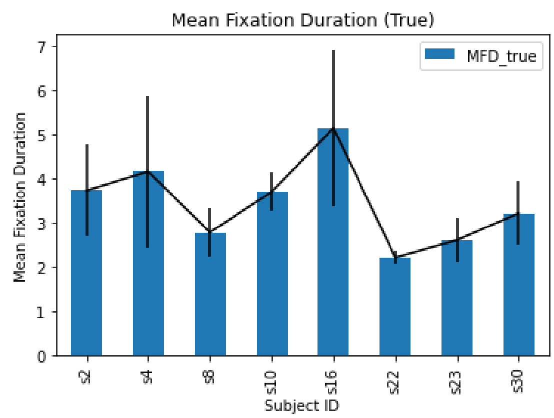

Figure 4: MFD(True), DT = 100ms

And then, we plot the same for MFD (False)

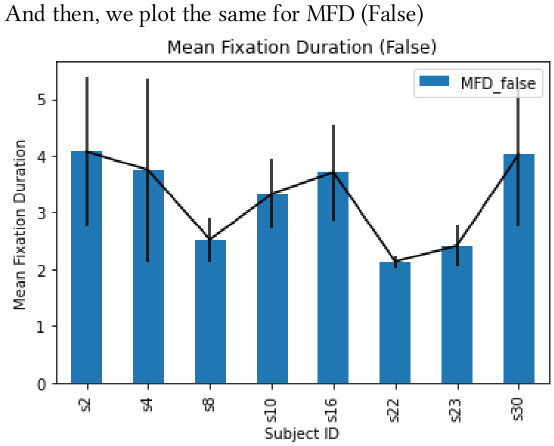

Figure 5: MFD(False), DT = 100ms

For the same algorithm, we will also plot the Mean Saccade Amplitude (True)

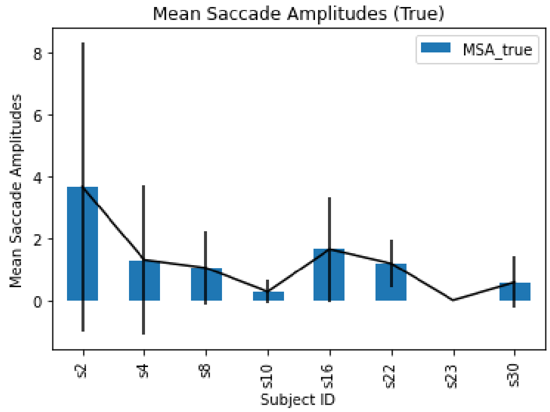

Figure 6: MSA(True), DT = 100ms

And the MSA(False)

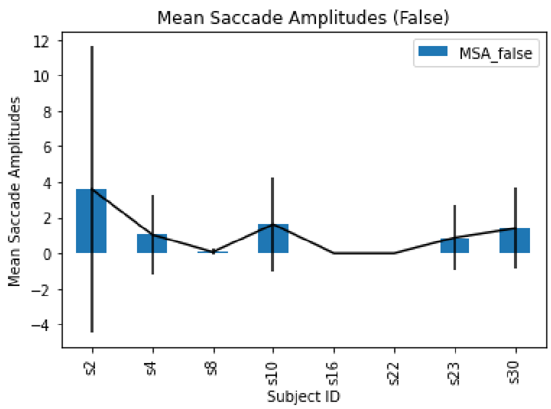

Figure 7: MSA(False), DT = 100ms

It should be noted that in the False case, some of the MSA were 0 or very close to it.

Finally, we plot the aggregate MFD and MSA as well

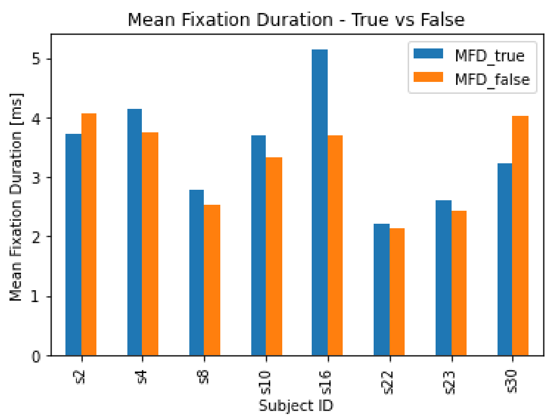

Figure 8: MFD(Aggregate), DT = 100ms

We observe that the MFDs in both cases were very similar to each other in all the subjects except for s16. It must be said that equal time was contributed towards each fixation to identify the image.

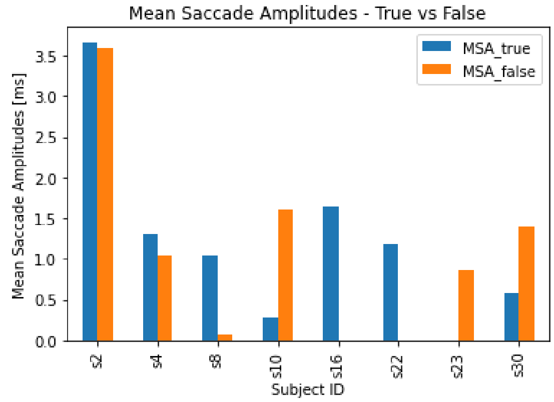

Figure 9: MSA (Aggregate), DT = 100ms

In many cases, we see that the MSA false is 0 while for subject s2, it is the highest in both cases.

It must also be pointed out that the 2nd subject has had gaze duration almost equal in the fixations as well as the saccades. Thus, almost uniform gaze all over the test field.

In subject s16, while the fixation duration was high, the saccade duration was low, thus all the gaze points was accumulated in groups and the member of the groups were very close to each other with no outliers.

4 Eye Tracking Data Capture (Part 2)

In this section of the Project, We record the eye tracking data using different test subjects with two different types of eye tracker devices which are mainly the gaze recorder for web browsing and the Tobii 4C/5.

The main idea of this data collection is to recognize the human pupil and record the movement and fixation when viewing images and websites. In our test, we calibrated the devices to specifically track which parts of the screen are being viewed which as a result generates a heat-map presented in the report with colors that represent where viewers focus their attention.

4.1 Gaze Recorder

GazeRecorder specifically works by measuring the intuitive gaze and Interactional behaviour from a test subject [1]. And this gives us information on how web reading occurs, identify problems and provide improvement solutions.

4.1.2 Result and Discussion

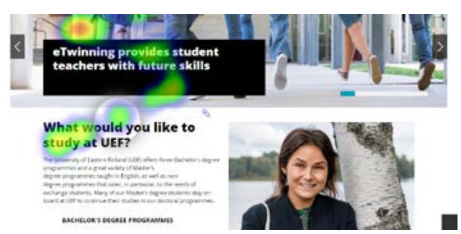

Figure : Heat-map

A conclusion has been drawn from the result with the idea that tends to identify areas that users spend the most time from the projected heat-map [1]. The point of interest for the participant as shown on the image was the text provided with potentials for a student. The participant paused as the point of while the automatic parallex schrolling continues. The participant was particularly interested in the text that is why the heat-map circled around the text region of the web page.

4.2 Tobii 4C

In this part of the project, we specifically design an Eye tracking experiment in the context of **Dementia test**. These tests are used to assess the thinking and physical functioning of an individual. The context of Dementia in our project is to find the correlations between eye tracking and dementia test results. In contrast to the short tests, there are only a few test batteries that are specifically tailored to dementia diagnostics. The standard is currently set by the test battery of the Consortium to Establish a Registry for Alzheimer's Disease (CERAD) [2][3]. This is also part of our project. All of our 4 test subjects have completed the test battery and were classified as not suffering from dementia. Accordingly, only qualitative conclusions can be drawn between eye tracking and non-demented subjects. Since there is no free test battery, a slimmed-down version was programmed by ourselves in the first step and hosted on the **website Wix**. Since a complete test run would exceed the time frame, this version has 5 questions in the areas of word fluency, naming and learning words.

4.2.1 Result and Discussion

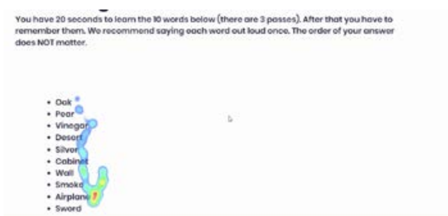

Figure : Heat-map

The above result which is one of the carried out experiment among the participant explains that, being the first pass, the participant as displayed on the hitmap focuses on the missing figure and write it down as it continues with the second pass. Based on the results we obtained, the gaze behaviour between participants differ significantly in the amount of time spent looking at areas of interest as well as the number of fixation made on some particular areas followed by the pattern of gaze movement.

4.3 Conclusion

In conclusion, eye tracking data capture is a valuable tool for understanding visual attention and cognition. By tracking the movement of the eyes, researchers can gain insights into how people process visual information, what they are paying attention to, and how their gaze behavior may vary across different tasks or contexts. However, it is important to keep in mind that eye tracking is just one tool among many and should be used in conjunction with other methods to fully understand human behavior. Additionally, it is important to carefully consider the limitations of eye tracking and how they may affect the interpretation of the data. By using eye tracking appropriately and in conjunction with other methods, researchers can gain valuable insights into human cognition and behavior.

Group Members Task Contribution (Project and Homework)

S/N	Group Members	Contribution (100%)
1.	Anna Braun	12.5%
2.	Raffael Rizzo	12.5%
3.	Abolfazl Jalali	12.5%
4.	Chihiro Tone	12.5%
5.	Uzairu Abubakar	12.5%
6.	Aryaman Sharma	12.5%
7.	Shani Israelov	12.5%
8.	Faria Ferdowsy	12.5%

5 REFERENCES

[1] Heer, J. Capturing and Analyzing the Web Experience. In CHI 2002 Workshop on Automatic Capture, Representation, and Analysis of User Activity, Position Papers, ACM Press (2002).

[2] Pullicino P. Bilateral distal upper limb amyotrophy and watershed infarcts from vertebral dissection. Stroke 1994;25:1870–2

[3] Bahill, A., Brockenbrough, A., & Troost, B. (1981). Variability and development of a normative data base for saccadic eye movements. *Investigative Ophthalmology & Visual Science*, *21*(1), 116–25.

[4] Project Description, Eye tracking 2022 Elearn

[5] Group 8 Homework - event detection part 1, Eye tracking 2022 Elearn

[6] U'n'Eye, https://github.com/berenslab/uneye