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Understanding the Language of the Eye: Detecting and Identifying Eye Events in Real  
Time via Electrooculography

A thesis submitted in partial satisfaction of the  
requirements for the degree of Master of Science

in

Computer Science

by

Rizwan Munir Ahmad

Committee in charge:

Professor James Hollan, Chair  
Professor William Griswold  
Professor Scott Klemmer

2016

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Chair

University of California, San Diego

2016

## DEDICATION

*Dedicated to my parents,  
Dr. Seema Munir and Dr. Jalil Ahmad*

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## ABSTRACT OF THE THESIS

Understanding the Language of the Eye: Detecting and Identifying Eye Events in Real Time via Electrooculography

by

Rizwan Munir Ahmad

Master of Science in Computer Science

University of California, San Diego, 2016

Professor James Hollan, Chair

The human eye has proven to be an enigma; a rich and complex organ that has not quite been fully understood. Naturally, this has caused the eye to be the subject of several medical and anatomical research efforts. More recently, the engineering community has used the eye as the inspiration behind the design and development of cameras, machine vision algorithms, and much more. In order to better understand the eye and its underlying patterns, the technique of electrooculography (EOG) was developed, in which electrical signals originating from the extraocular muscles are measured. The development of EOG has recently opened a new line of research within the engineering disciplines, due to its

potential use as an input mechanism for computers and software applications.

In this thesis, I use a pair of Jins Meme glasses, a lightweight and commercially available EOG system, to build a realtime classification system capable of detecting and classifying blinks and movements in the eye. In addition to analyzing the realtime classification system and its inner workings, I use this system to investigate the potential uses of EOG within the realm of Human Computer Interaction. In doing so, I find optimistic results — the classification system was capable of properly classifying 89.7% of directional eye events and blinks in a set of control datasets. I additionally present two real world use cases for EOG and describe a series of improvements and future work that could aid in advancing the future of EOG.

# Chapter 1

## Introduction

From the rise of the trackpad, which revolutionized the laptop industry, to the advancement of touch and multi-touch screens, which aided in the dramatic growth of the smart phone industry, new reliable input modalities have the potential to lead to significant technological advances. As a result, a significant amount of research energy has been put into creating input modalities that allow for more natural interaction with users. One such category of input modalities that is becoming more relevant are those that make use of the human eye.

As vision is a human's primary sense for obtaining and processing information about the world around it, the eye provides a wealth of information about us. Previous research has shown that monitoring movement in one's eyes can detail the focus of one's attention [6], aid in diagnosing and recognizing certain health conditions [13], and even provide information regarding the activity in which a person is currently engaged [11, 56]. However, despite the sheer abundance of information that is present in the eyes, eye-based interaction techniques have not become particularly relevant in technology today. This is due to a variety of reasons, such as the difficulty in differentiating between eye interactions and natural eye movement by the user, as well as relative inaccuracy and lack of portability of eye tracking technology. As such, the eyes currently represent a largely untapped source for innovation.

Electrooculography (EOG) has been shown as a potential way to track a person's eyes in real-life settings. EOG works by monitoring electric signals originating from the extraocular muscles which control the eye, much like electroencephalography (EEG) does with the brain or electrocardiography (ECG) does with the heart. Historically, EOG has been used primarily in medical settings and largely stayed out of the technology realm, which concentrated more on traditional eye tracking systems. Recently, EOG technology has become much more refined and less "lab-reliant" as other biosignal technologies. These advancements, however, have still not brought EOG to the forefront of eye-based interaction technologies, and much work within the realm of EOG remains to be done.

In this project, I investigate the efficacy of electrooculography in real life settings. To do this, I build a demonstrative classification system that detects motion and blinks in the eye in realtime and provides the direction of the movement. Additionally, to further demonstrate the potential power of EOG, I present two case studies which showcase different aspects of the data that can be obtained from EOG systems. I additionally evaluate the EOG technology used in this project, the Jins Meme glasses [39].

This thesis is divided into 9 chapters. Chapter 2 provides further background as well as an overview of related work pertaining to EOG, eye-based interaction, and other associated topics. In chapter 3, I provide an overview of the Jins Meme glasses and its strengths and drawbacks. Chapter 4 explores the realtime classification system, how it was built and run, and its performance on control datasets. Chapters 5 and 6 introduce two case studies; one a system that reads EOG data and graphically displays the movements on a computer and the other a brief exploration into modeling and recognizing activities via EOG data. Chapter 7 discusses the outlook of EOG and the Jins Meme glasses given the experiments and data received in the project. Finally, in chapters 8 and 9, the project is concluded and potential avenues for future work are discussed.

# Chapter 2

## Background and Related Work

Electrooculography is an interdisciplinary field that encompasses topics from several different related disciplines. In this section, I provide background and identify related work in these fields.

### 2.1 Studies of Eye Activity

Eye activity is typically divided into two different categories: saccades (movements) and fixations (stops). Young and Sheena in 1975 and Morimoto and Mimica in 2004 both performed in depth analyses of different techniques in recording and analyzing eye movements [52, 63]. This includes a variety of forms of optically tracking the eye (e.g. via the use of Purkinje images or the limbus), tracking via contact lenses, as well as electrooculography. It is worth noting that, in Morimoto's paper, EOG is described as an "intrusive, but simple and low cost" form of eye tracking. It is my belief that EOG nowadays, especially with such up and coming technologies as the Jins Meme glasses, is no longer an intrusive form of eye tracking, and that future revisions of EOG systems will further cement its place as a primary eye tracking solution.



### **2.1.1 Optical Eye Trackers**

The most popular way of monitoring eye activity, especially outside the realm of medicine, is via the use of optical eye trackers. These can take several different forms, such as those that track the first and fourth Purkinje images (i.e. specific manifestations of glare) on the cornea [16, 17], the iris-sclera boundary (limbus) [18, 33], or the pupil-iris boundary [53, 67].

While perhaps the most accurate, tracking of the Purkinje images is rather problematic due to the system being very intolerant to head movement as well as the process being very user- and training-dependent. Limbus trackers, on the other hand, suffer from the issue of being notoriously poor at modeling vertical movement due to the vertical extremes of the limbus being occluded by the eyelid. As such, pupil trackers have recently become the most widely used trackers. This, however, also suffers from the pupil not necessarily being readily differentiable from the iris surrounding it. In order to solve this, people have adopted a variety of techniques, most notably using infrared light in order to “brighten” the pupil via the red-eye effect [54, 66].

Perhaps the largest issue with optical eye trackers, however, is the fact that they require being in a setting with a properly placed camera that requires constant calibration. This fragility does not lend itself well to most everyday use cases, especially those that extend beyond the use of a computer. This is one of the primary factors in my motivation behind studying electrooculography in this thesis.

### **2.1.2 Correlations**

One of the more interesting facets of eye tracking, as it pertains to this work and future work, are the correlations that exist between eyes and other parts of the human experience. In work performed by Bruneau and Ehmke, activity in the eyes can be used as a proxy for cognitive attention, and can therefore be used as a feature in piecing

together what a person was focusing on at a given time [6]. Along these lines, studies have additionally shown correlations between specific eye responses, such as pupillary dilation, with cognitive load [2, 3, 44]

A few other correlations that have been found include those between eye events and alertness [32], mouse movements [14], and even temperature changes [60].

## **2.2 Electrooculography**

The field of electrooculography dates back to the 1849, in which du Bois-Reymond demonstrated the existence of an electric potential difference in the front and back of the eyes of a freshwater fish [24, 50]. After this initial discovery, further studies into the subject were performed, with the beginnings of the modern electrooculogram being made in the 1930s by Edmund Jacobson [35].

### **2.2.1 Medical Use**

Electrooculography has primarily been used in the medical field, with several studies of the eyes making use of EOG. Through the early- to mid-20th century, many of the uses of electrooculography, and many of the canonical studies that pushed the technology forward, were focused on medical applications, such as visual fatigue [12] and modeling of the extraocular muscles [55].

More contemporarily, EOG has been used in a variety of fields of medicine. It has found uses in monitoring visual development and acuity in children [19, 20], sleep studies [57, 62], and has been used in studying and diagnosing several different disease states [4, 13, 22, 27, 43].

With its wide range of potential applications, Brown et al. from the International Society for Clinical Electrophysiology of Vision (ISCEV) came up with a standard for EOG in clinical settings [5], which has been updated as recently as 2010 [51]. Despite

this and the potential applications, however, EOG has still not become a staple in medical practices, likely due to the lack of simplicity in quickly understanding the data, and significant amounts of noise and confounding factors.

## **2.3 Potential Applications for Eye Tracking**

Within the technology realm, eye tracking in recent years has shown a great deal of potential, with optical eye tracking input interfaces becoming much more sophisticated and readily available. Such eye trackers have been shown to have use cases in computer security and privacy [21, 26, 45], design [25, 61], and, of course, human-computer interaction [31, 41].

EOG specifically, though, has only become more prevalent in the technology field recently. Despite this, there have already been studies showing EOG's effectiveness, such as research on EOG-based controllers for wheelchairs [1] and robotics [15]. Within the HCI community, Bulling et al. have performed a series of studies on EOG, which have looked into eye-based activity recognition, with an emphasis placed on reading [10, 11], as well as the eye's applicability as an quick and mobile input modality for computing applications [7, 8, 9].

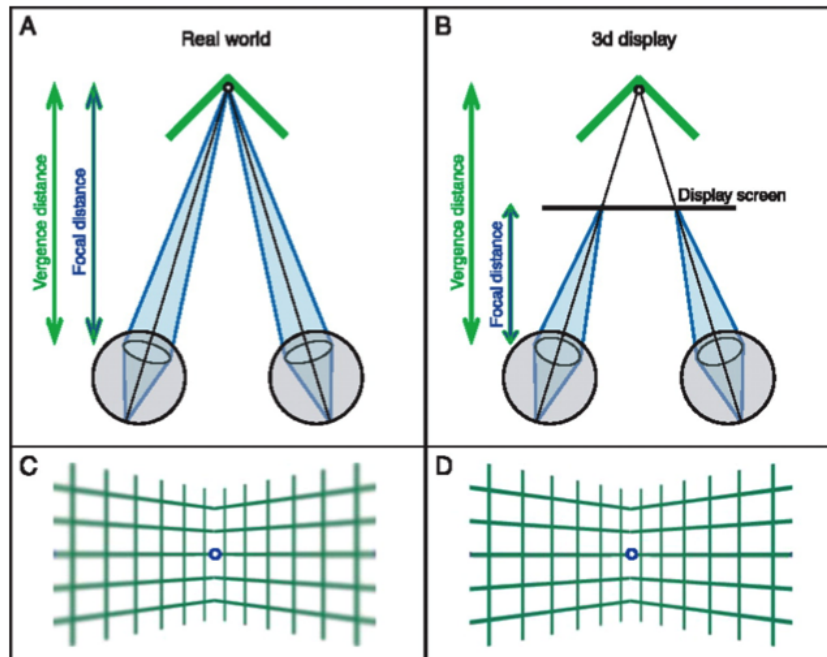
### **2.3.1 Augmented Reality and Virtual Reality**

Two areas that I believe align greatly with EOG, but have largely not been connected to it in the research realm are the fields of augmented reality and virtual reality. It is likely that virtual reality headset manufacturers have looked into EOG as an input source - in fact, there was a post on EOG in the Oculus Rift forum in 2013 [28] and Palmer Luckey, founder of Oculus VR, commented on a Reddit post in which he directly mentioned electrooculography [49] - but it seems that EOG signals were not used in the recently released Oculus Rift.

It is my belief that both augmented and virtual reality interfaces could be greatly improved with EOG. By using EOG as an input modality, it would greatly increase the ability and efficiency for a human to interact with such headsets, and they would be more accommodating to those who are perhaps less dextrous with their arms. It would also allow for less distracted interaction in the case of augmented reality interfaces in settings such as cars, as the person would no longer need to take their hands off the steering wheel in order to interact with the car.

Additionally, using EOG could potentially provide a solution to the vergence accommodation conflict, a source of virtual reality sickness [30, 58]. When perceiving distance, human eyes have two separate processes that come into play - vergence and accommodation. Vergence refers to the process in which the two eyes move opposite to one another in order to maintain single binocular vision. This is perhaps best illustrated by focusing on a pencil or a finger as it is moved closer and further from a person's eyes - when moving closer to the face, the person's eyes will naturally converge towards the nose, while when moving away, the eyes will begin diverging toward the center point of each eye. Accommodation, on the other hand, refers to the process of changing optical power to focus on objects at different distances.

Three dimensional displays (such as those in virtual reality headsets) "trick" the eyes into perceiving distance through artificially resizing items or blurring those that are "out of focus." In doing so, though, these displays throw off the alignment of vergence and accommodation, as can be shown in Figure 2.1, resulting in virtual reality sickness. However, with EOG, it would potentially be possible to track the eyes as vergence naturally occurs and constantly reposition the screen image in order to alleviate the effects of vergence accommodation conflicts.



**Figure 2.1.** Diagram exhibiting the vergence-accommodation conflict (from [30]).

## 2.4 Jins Meme

The Jins Meme glasses [39] are a set of electrooculographic glasses which greatly reduce the footprint and size of typical electrooculographic devices, thereby improving portability. They are, however, largely untested when it comes to real world applications. Manufactured by Japanese company JINS CO [36], they have been marketed with a series of phone apps that allow for a variety of utilities including general logging, evaluating running and core body exercise form, and drowsiness monitoring [38]. Most of these apps, though, do not make use of the electrooculographic sensors, and instead make use of the accelerometer and gyroscope built into the glasses.

From the electrooculographic side of the glasses, JINS has been actively promoting academic research utilizing their glasses. As a result of this, there have been a series of papers published that make use of the Jins Meme glasses, focusing on the following subjects: the development and inner workings of the glasses [40], counting words read

by a user [47], posture analysis [46], and activity recognition [34].

A full breakdown of academic efforts involving the Jins Meme glasses can be found on the Jins Mem website [37].

# Chapter 3

## Jins Meme Glasses

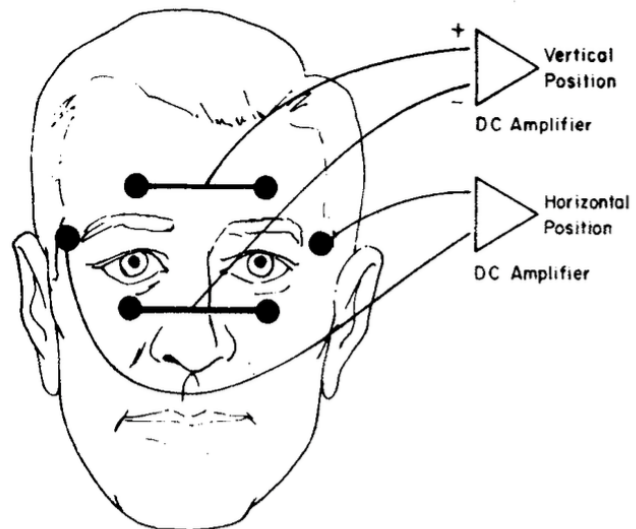
### 3.1 Strengths and Weaknesses

The Jins Meme glasses proved to be a very unique EOG collection system. While most research and studies involving EOG tend to involve either custom made lightweight EOG apparatuses or large, medical grade sensor setups, the Jins Meme glasses are a simple-to-acquire, commercially available pair of glasses. This, to me, is extremely advantageous in and of itself as one of my primary objectives in this study is to see how viable EOG technologies are in real life settings. The Jins Meme glasses help achieve this goal as they are a very good showcase of a product that could realistically be used by everyday individuals. Additionally, they help show that larger, more sophisticated EOG systems are not required to extract meaningful trends from EOG data. That said, the Jins Meme glasses do suffer from the following drawbacks.

**Electrode Placement** Figure 3.2 shows the classic placement of EOG electrodes. Typically, they are placed on the left and right sides of the eye as well as above and below. The electrodes on the vertical axis are meant to identify vertical movements of the eye, whereas those on the horizontal axis distinguish horizontal movements. In the Jins Meme glasses, though, there is only one electrode per eye, which is placed on the medial side of each eye, as can be seen in Figure 3.3. While this is



**Figure 3.1.** A photograph of the Jins Meme Glasses.



**Figure 3.2.** Electrode placement on typical EOG apparatuses (from [63]).





**Figure 3.3.** Electrode placement on the Jins Meme Glasses. The nose bridge serves as the ground reference node and the two nose pads act as the actual voltage reading nodes.

still able to fairly accurately model horizontal movement, it increases the amount of noise in the data, as there is only one point of contact rather than two. As for vertical motion of the eye, I was able to identify patterns which corresponded to upward and downward movement of the eye, but was unable to accurately track the position of the eyes on the vertical axis.

**Movement of Glasses** As mentioned above, since the glasses only had one electrode per eye, there was a fair amount of noise in the data. The noise was exacerbated, though, by the fact that the glasses do not stay in a single place while wearing them. Instead, they tend to either move around naturally, by sliding off or being pushed by facial expressions, or are artificially adjusted by the user themselves. As this causes the electrodes to also move around, extra skew and noise is introduced to the data.



**Figure 3.4.** Wear and tear on the USB cover of the Jins Meme glasses.

**Fragility** From the perspective of evaluating the glasses from an “everyday, average item” perspective, the glasses also suffered from some construction issues. While Jins Meme does offer a few different models of glasses, the ones that I used were simply made of plastic and felt rather fragile and flimsy. After just a few weeks of regular use, the cover of the charging port was dislodged - as seen in Figure 3.4 - and the covers at the end of the frame could easily be taken off. Overall the feel of the glasses was somewhat unappealing, though, again, this a subjective opinion, and, even then, is a minor issue that could easily be remedied over the course of further iterations of glasses.

**Discomfort** Another, perhaps more important, non-technical issue regarding the glasses, was their comfort level. While the aesthetic appearance, as mentioned above, is a rather minor issue, I do believe that the feel is an important feature for any product, and especially for a pair of glasses. From personal experience, wearing the glasses

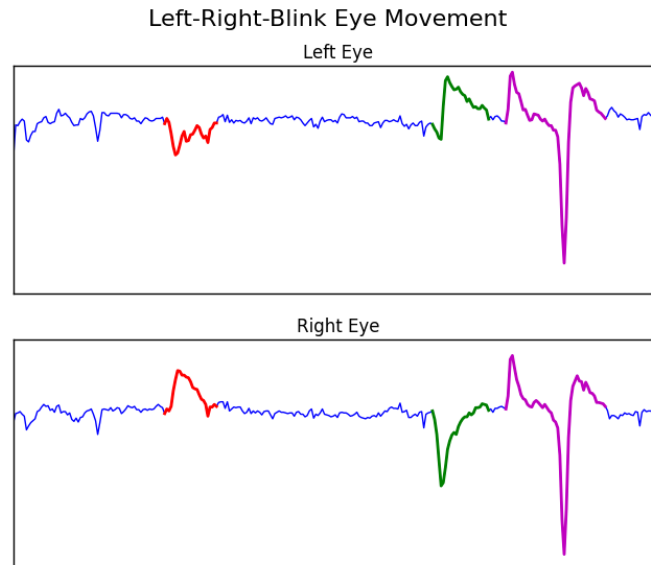
for extended periods of time caused a fair amount of fatigue and discomfort, and I had to take regular breaks from wearing the glasses in order to recover.

Despite these drawbacks, it was found that the system worked quite well. While not perfect, the data allowed for eye events to be detected and classified reliably. Additionally, as will be discussed more in Chapter 4, the data was still able to be classified with minimal amounts of filtering and cleaning, which I find rather surprising, given the potential sources of noise mentioned here.

Another interesting aspect of the Jins Meme glasses is the presence of a three-axis accelerometer and gyroscope. The data from these sensors were not used in this project due to the data from these sensors not being directly applicable to the eye events studied (directional movement and blinks). Upon visual inspection, though, they also seem to carry a fair bit of information which could be used to aid in reducing noise due to head movements as well as lead to more robust classifiers.

## 3.2 Jins Meme Data

Interestingly, while the EOG data observed from the Jins Meme glasses clearly captured movements of the eye, the shape and trends in the data were not found to be a very good indicator of the *position* of the eye. This runs contrary to the findings of other researchers using EOG setups, who found that, since there is always a muscle that is pulling the eye in a particular direction, the EOG data could be used to determine the position of the eye even at rest. However, by looking at a simple eye event, such as that in Figure 3.5, it can be seen that the Jins Meme data is not able to recreate that; the figure shows an example of a simple event in which the eyes move to the left, pause for a moment, move back to the center, and then blink. As can be seen in the period between the red and green portions of the graph, which symbolize the left and right



**Figure 3.5.** Example of a subject moving their eyes to the left, back to the center, and then blinking. The top graph shows the signals of the left eye and the bottom shows those of the right eye. The leftward movement is highlighted in red, the rightward movement in green, and the blink in magenta.

movements respectively, the pause at left extreme of the eye socket is not represented in any discernable way. Instead, it is represented by what appears to be a return to the baseline in between the two peaks.

Given this, it appears the peaks do not model the position of the eye, but rather correlate to the electrical spike of the action potential that generates the mechanical contraction of the eye muscles [59]. While this could be somewhat concerning, as this does not model the position of the eye, a measure of the action potential is equally as useful, as the strength of an action potential can be correlated to the strength of a muscle contraction [48]. Thus, since the muscle contraction is what physically moves the eye, it can therefore be concluded that the strength of the action potential can approximately model the velocity with which the eye is pulled in a given direction. This idea is backed up in the first case study of the project.

It is still possible, however, that the more “traditional” EOG data which corresponds with the position of the eye is still present in the Jins Meme data, and simply requires more fine-tuned data analysis in order to be accurately portrayed.

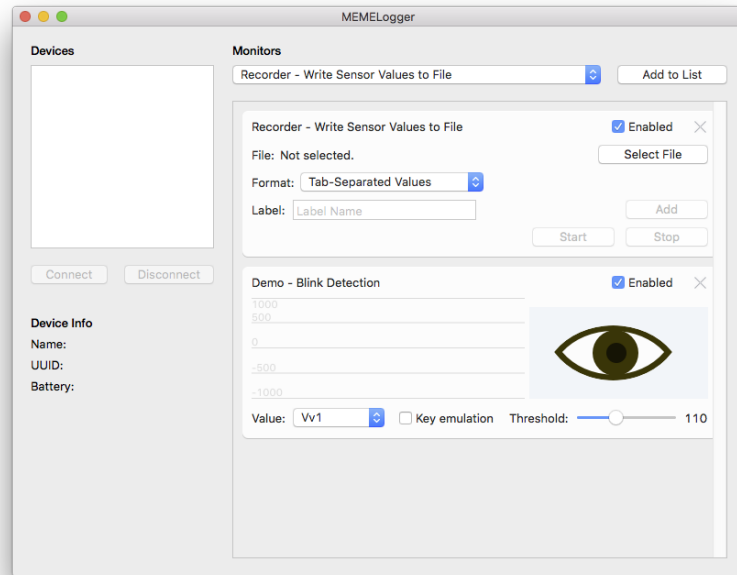
### **3.3 Data Collection**

The Jins Meme glasses contain a Bluetooth Low Energy (BLE) module that allows it to transmit data to external devices. The consumer version of the product allows users to connect to iOS and Android apps which provide various pieces of functionality ranging from monitoring running form to detecting signs of drowsiness while driving. For academic use, the glasses came with an application that allows access to the raw data being transmitted from the glasses. This application, titled the *MEMELogger*, allows users to display the current values of the glasses’ sensors, stream the data to a file, or play with a series of predefined demos. A picture of the application can be seen in Figure 3.6.

Due to the easy access that the MEMELogger application provided to the data from the glasses, I did not focus on building Bluetooth drivers to communicate with the glasses and receive data in realtime. Rather, I would use the MEMELogger application to stream the data from the glasses to a data file, which would then be used to pass data to the classification system. By doing this, I was able to prioritize work on the classification system rather than these supporting systems. I was also able to guarantee a more portable and universally accesible system, as creating a communication module for the glasses was bound to be very platform and system-dependent.

#### **3.3.1 Datasets**

To assess the accuracy of the classification system, I recorded several control datasets. While this is not the same as “real” data, I felt it did a good job of establishing the fact that classification can be done, and that future efforts will be able to better deal



**Figure 3.6.** Screenshot of the OSX MEMELogger Application used with the Jins Meme Glasses

with the noise and erroneous information that comes hand in hand with real world data. The recorded datasets were made as a combination of simple movements in repeating patterns. For example, one particular dataset involves blinking, followed by moving the eyes to the left extreme, back to center, then to the right extreme. By creating a series of these datasets, each modeling a different chain of movements, I was able to ensure that the classifier was able to pick up blinks as well as movements in all four directions. I was also able to determine whether or not certain movements caused issues for the classifier, and remedy these “confusing” cases accordingly.

While recording myself with the EOG glasses, I also took video footage of the recording session. In doing so, I was able to better assess accuracy by comparing the output of the classifier with the actual footage of the recording session.

# Chapter 4

## Realtime Classification System

The realtime classification system that I built for this project was split into two different modules - one which identified when an eye event (i.e. blinking or moving the eye up, down, left, or right) occurred, and one which labelled each event with what the predicted event was. In the next sections, I discuss the inner workings of these modules and provide commentary on the successes and shortcomings of the system as a whole.

From a technical perspective, both systems were programmed in Python, using various libraries including NumPy [23] and HMMLearn [29]. While these did the job for this project, it should be kept in mind that the time performance of the system could potentially be greatly improved if the system was programmed at a lower level (e.g. in C or Java), and if libraries were not used. Algorithms built specifically for this application could also potentially lead to higher accuracy ratings as well.

### 4.1 Event Detection

The first revision of the classification system was not meant to be separated into two parts. Rather, seeing as how the EOG data was a time series dataset, I simply set out to try and use a hidden markov model (HMM), the de facto “gold standard” of time series analysis tools, to distinguish between the different eye events. HMMs work by identifying a given number of hidden “states” in a dataset and inferring the probability

of a data point being in a specific state given the previous sequence of data. In this case, I attempted to have the HMM model each individual eye movement, blinks, and the baseline. However, this proved largely unsuccessful; the HMM suffered greatly in distinguishing between the different events, often simply dividing the dataset into separate chunks, rather than identifying different states, as can be seen in Figure 4.1. In the figure, it can be seen that, while the “magenta” state is able to pick up some spikes (i.e. some eye events), the other states come around seemingly randomly and do not model anything in particular. It is possible that a supervised model could potentially have done better, but I chose to avoid supervised learning models for this project due to the need for a large dataset of carefully labelled data, which I did not have.

After reaching the conclusion that the HMM would not work as a way of classifying an eye event, this task was abstracted to a separate module which was designed later in the project. The HMM, meanwhile, switched roles slightly and was used to determine *when* an event occurred. In this scenario, the HMM only has to distinguish between two different states - the baseline and the occurrence of an event. It should be noted that the EOG data has very definitive spikes when an event occurs. Thus, by feeding the HMM the derivative of the data - that is, the difference between the “current” point and the previous point - the HMM is able to fairly consistently determine if an event is occurring. The HMM’s ability to identify eye events can be seen in Figure 4.3, which shows the same data from Figure 4.2 with labelling provided by the HMM.

## 4.2 Data Preparation

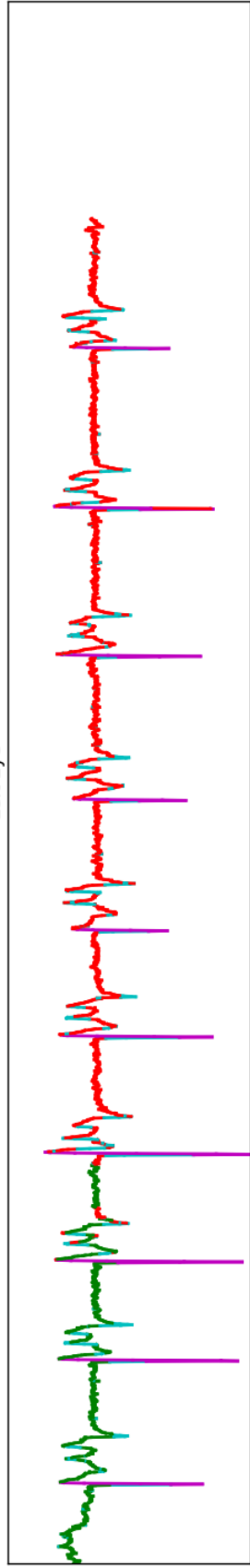
Since the data was naturally fairly noisy, there was some data preparation that was necessary in order to prevent false positives from being detected by the hidden markov model. To do this, the hidden markov model was first run without any filtering in order to see what the common pitfalls were. The main issue that was noticed was the HMM



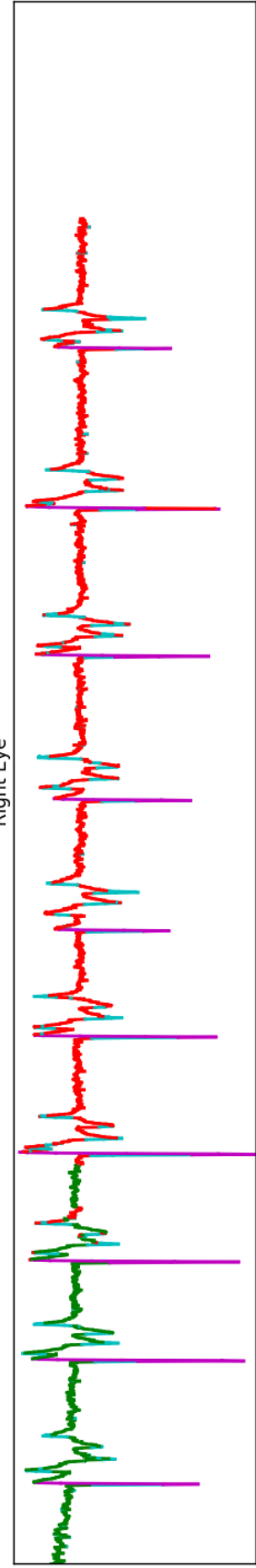
**Figure 4.1.** Example of the labelling of states performed by the hidden markov model when four states are used. Each color represents one state and the position of each color on the graph represents the points that were labelled with that state.

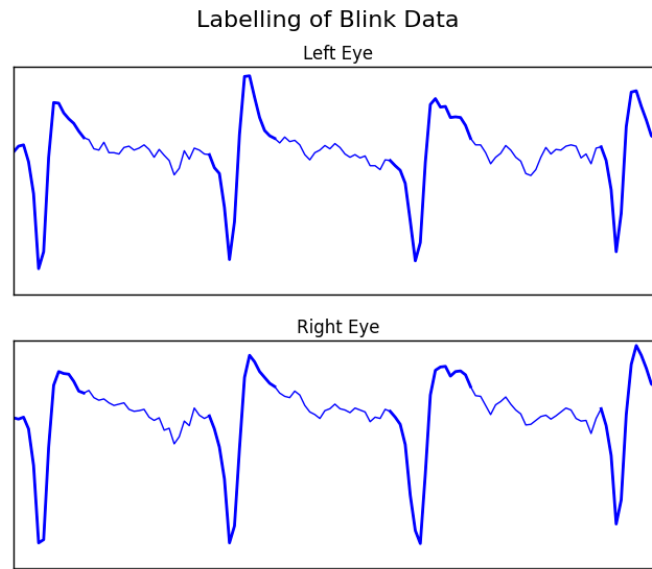
### Hidden Markov Model Labelling With Four States

Left Eye

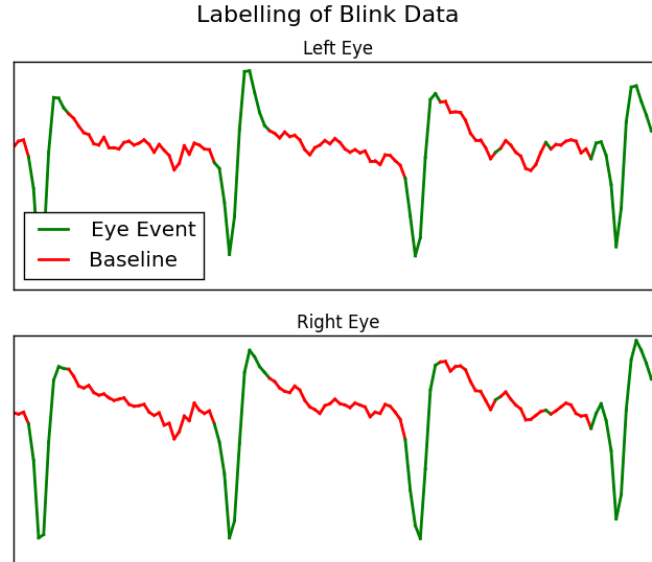


Right Eye

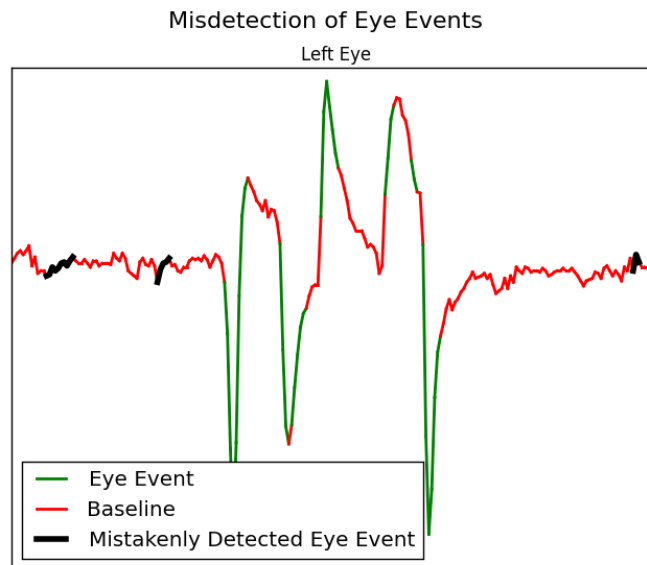




**Figure 4.2.** An excerpt of a dataset containing a series of four blinks. The blink events themselves are highlighted for ease of viewing.



**Figure 4.3.** The same data from Figure 4.2 after being run through the hidden markov model. The green parts of the line are the areas that were identified by the model as being potential eye events.



**Figure 4.4.** An excerpt from a dataset showing mis-detections by the hidden markov model prior to data filtering.

picking up small hills and valleys as legitimate eye movements. An example of this can be seen in the black labelled parts of the graph in Figure 4.4. In order to account for these, when running the hidden markov model, any data point in the derivative that was within a certain threshold from the calculated baseline (a running average of non-marked data points) was normalized to the baseline. In doing so, small deviations from the baseline were either cut out entirely, or were kept small enough that the markov model did not mark them at all.

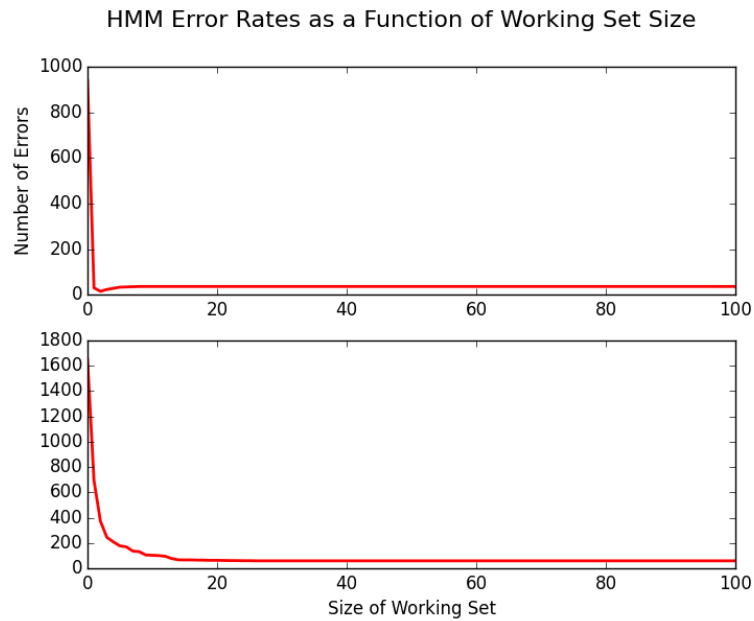
From a more context-aware standpoint, while it is likely that small deviations are noise in the data, it is also possible that some of these were micro movements of the eye, or stabilizations for movements of the head. While this was not explored in this project, it would be an interesting area to explore further.

### 4.2.1 Working Set of Data

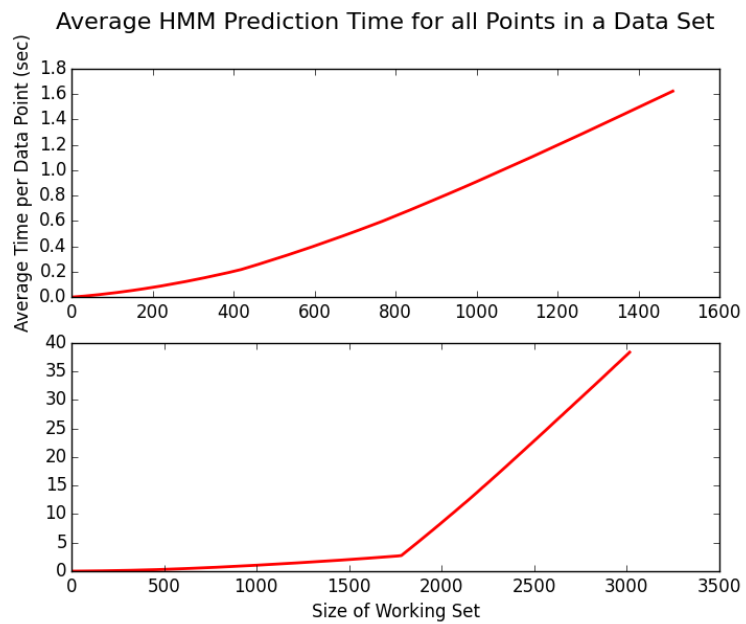
As the EOG data comes in in realtime, the HMM prediction has to be run constantly on each new data point as it arrives. This was somewhat problematic, though, as running the prediction through the markov model is still a fairly computationally intensive operation, and its time complexity is directly dependent on the size of the sequence length [42], which, in this case, is potentially infinite. Thus, especially with the fairly fast sampling rate of the glasses, the running time of the HMM had to be kept as small as possible. In order to mitigate the time concerns, it was decided that the historical context given to the HMM when running a prediction for any given point would be limited to a very specific working set of previous data points.

The next issue that naturally arose with the use of this working set, however, was what the proper size of the working set should be in order to sufficiently reduce running time while maintaining accuracy. In order to determine the optimal size, an experiment was run in which the HMM was run on a series of control datasets, each containing different combinations of events, with varying sizes of working sets, and the prediction results obtained from each run was compared to the predictions made by the same HMM with full context. The average time of the prediction task on each point was also logged, allowing a proper comparison between the accuracy and running time of each context size. The results from this experiment is shown in Figures 4.5 and 4.6.

Figure 4.5 shows that the accuracy of the markov model did not improve at all when the size of the working set grew beyond 30. It was also seen that the running time shows definite increases as the working set increases in size. As the experiment was far from exhaustive, and there could be (and likely do) exist datasets in which the maximum accuracy is only achieved with working sets larger than 30, a size of 50 was chosen for this project. The tradeoff in running time for this increase in size was deemed acceptable



**Figure 4.5.** Relationship between Working Set and HMM Error rate for two different datasets. Note that further measurements were taken beyond a set size of 100, but due to the lack of any improvement, these samples were left out.



**Figure 4.6.** Relationship between Working Set and HMM average prediction time for two different datasets.

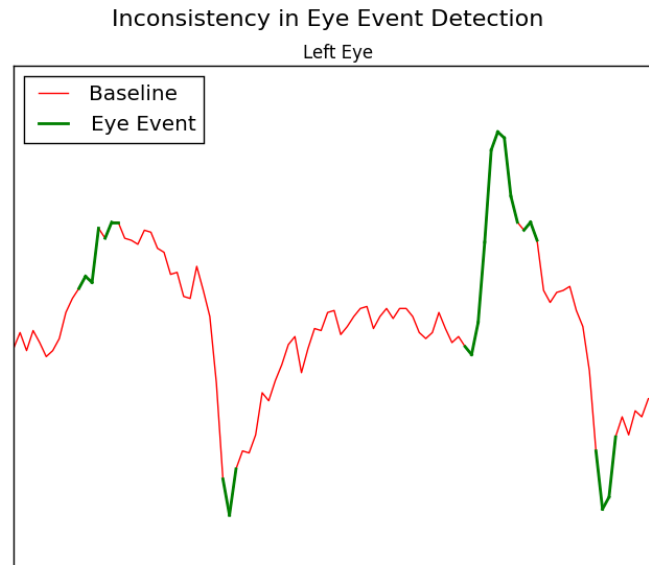
for the amount of buffer it would provide for those datasets which require larger working set sizes.

#### 4.2.2 Commentary

Use of a hidden markov model did work surprisingly well for identifying when eye events occurred. Out of the several datasets that were recorded, the HMM missed only six eye events out of a total of 253 events, though it did have 43 false positives. This correlates to a 2.4% false negative rate and a 16.9% false positive rate.

One issue that came up, which could explain the large amount of false positives, was the hidden markov model splitting one real event into multiple events, typically with one or two “baseline” points in between. In Figure 4.7, the large upward spike - which models one event - demonstrates this issue, since the spike contains a small portion of red line (the baseline state) between two green lines (the event state). This signifies that the HMM believed this event to be two separate events rather than one large event. In order to deal with this issue, I decided to link together events detected by the HMM that were only separated by a single “baseline” point - effectively treating them as one continuous event, though this was not a perfect solution as can be seen by the fairly high false positive rate.

Another issue that arose with the hidden markov model was consistency in the start and end times of an event. That is, oftentimes, the HMM would detect an event late or end an event early. An example of this can be seen in Figure 4.7. In this figure, there are four events depicted - two leftward movements symbolized by the two maxima and two rightward movements symbolized by the two minima. By comparing the first leftward and rightward movements with the second two movements, it can be seen that the first ones are much less optimally highlighted, with both of them starting later and ending earlier than their later counterparts.



**Figure 4.7.** Issues in events detected by the hidden markov model.

It is possible that this was artificially introduced due to the data filtering steps that were put into place. However, all in all, this did not cause much issue for the classification task, and it was therefore ignored. It did become an issue later, though, when I attempted finer-grain eye tracking in the first case study, as the model was somewhat unreliable in properly tracking the change in position of the eye.

One area that was again somewhat overlooked in this project was the use of a different model, whether it be a markov model based on a different distribution, or even a classifier that runs as a helper to the markov model. It would be interesting to go through the math and determine a better model, but as far as this project is concerned, I was fairly happy with the performance of the HMM - it was able to do its job with some very minute caveats that could perhaps be remedied with further insight into the EOG data.



## 4.3 Event Classification

The event classification system of the prediction task, in my opinion, is a slightly more interesting problem, which brings with it several different potential solutions. Whereas the event detection task was a fairly straightforward time-series data analysis task, which to some degree lent itself well to the use of hidden markov models, the classification task has many more possible approaches. That said, testing different classification algorithms and their performance was deemed to be a slight tangent for this project, and was therefore not explored in great depth.

### 4.3.1 Classifier

Currently, the classification algorithm takes in points of data that have been marked by the hidden markov model, and finds the area under the curve for those points. By monitoring the positivity and negativity of this area over time, the classifier is able to match the current pattern with a predefined set of patterns for the four eye movements as well as blinks. The classifier additionally auto-corrects itself as more data becomes available in case the current pattern changes. The classifier also ignores any marked sections of data that only encompass a single point, as these are indicative of false positives picked up by the HMM.

The presence of only medial electrodes does cause some issue in the tracking of vertical eye movements. While the electrodes are not able to accurately track position of the vertical eye movements, I am still able to determine when vertical eye events happen, due to the nature of vertical movements. For lateral movements, the eyes are moving in opposite directions with respect to the electrode. For example, when looking to the left, the right eye moves closer to the electrode, while the left eye moves away from it. From the perspective of the electrode, this causes the two eyes to send opposite signals. When

**Table 4.1.** Descriptions of the effects of eye events on the left and right eye EOG signals

Eye Event	Left Eye EOG Signal	Right Eye EOG Signal
Look Left	Drops	Rises
Look Right	Rises	Drops
Look Up	Drops	Drops
Look Down	Rises	Rises
Blink	Drops then rises	Drops then rises

dealing with vertical movement, however, the two eyes move in the same direction with respect to the electrode, thus allowing me to pick up on this movement. Table 4.1 shows the patterns for the four eye movements as well as blinks.

### 4.3.2 Commentary

As was mentioned previously, classification tasks are classic problems in data mining, and there are nowadays several of algorithms and methodologies for tackling them. It is very possible that using a support vector machine (SVM), or even a simple linear regression could provide an improvement in both the accuracy and scalability of the classifier in this project. It is worth noting, however, that the current classifier still has the added benefit of not requiring any sort of training set, which makes it extremely portable and user-independent in contrast to these other methodologies. That said, the need for a training set is an overcomeable issue with calibration tasks for the user.

However, all in all, I was again happy with the results of the classifier. It is for sure not a perfect solution, with very clear limitations especially outside the realm of the control datasets upon which it was being run, but it serves, in my opinion, as a good first step and proof of concept of the ability to properly classify EOG data into distinct movements.

As for accuracy, over a total of 253 eye events recorded in the control data sets which were deemed to not be false positives, the classifier was able to properly classify

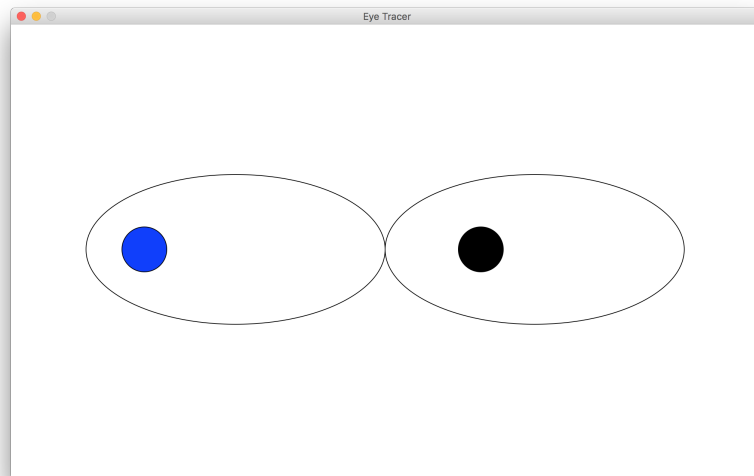
227 events, leading to an overall accuracy rate of 89.7%. It is worth noting, though, that this was received on fairly controlled datasets with very distinct eye motions, and that real world data showed significantly reduced accuracy rates, which are discussed in Chapter 6.

# Chapter 5

## Case Study: Graphical Eye Tracer

One of the most pertinent proofs of concept for any eye tracking application or technology is the ability to model movements of the eye. In this section, I describe an extension of my Jins Meme EOG classification system which generates a graphical model of an eye, showing the movements made by the eye for a given dataset. This is meant to demonstrate a potential application which can be greatly simplified with the use of the realtime classification system described in the previous section. A screen shot of the eye tracer can be seen in Figure 5.1.

As was mentioned previously, the peaks that were the basis of the classification of eye events were found to correlate more closely with the strengths of the action potential that generated eye movements, rather than the position of the eye. Thus, this case study also indirectly presents the idea that the eye movements can still be accurately depicted by using the strength of the action potentials as a model of the strength of the eye's muscle contraction, thereby modeling the velocity with which the eye moves. Given that the electrodes on the Jins Meme glasses are meant to record lateral movement rather than vertical movement, the eye tracer in its current form only models this horizontal movement. I am optimistic, though, that the vertical movements can also be modeled with some further work.



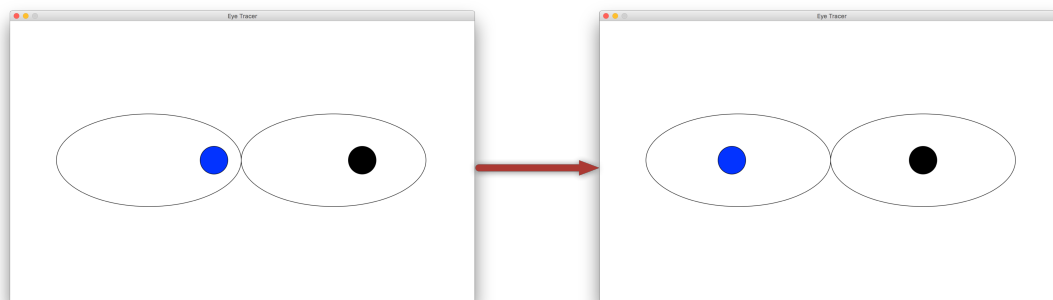
**Figure 5.1.** Screenshot of the Eye Tracer.

## 5.1 Methodology

The eye tracer is a Python program making use of John Zelle's Python Graphics Module [64, 65]. An EOG dataset is run through the realtime classification system, which outputs a set of labels for each data point corresponding to what eye event is currently happening at that data point, if any.

Since the EOG data is being treated more as velocity data rather than position data, the next step in building the eye tracer was to be able to model the position of the eye during a given eye event. To do this, the data is reanalyzed, and the integral of each detected eye event is computed, giving a model of the position of the eye. This is done on the raw data, rather than the baseline-normalized data that was used by the hidden markov model and classifier in order to ensure higher accuracy. With this information, the maximum and minimum integrals are recorded and are used as the reference points for the extremes of the eyes. It should be noted, though, that by doing this, it is assumed that at some point in the data, the user reaches for the extremes of the eyes.

The integrals of all the other events are then normalized against these reference



**Figure 5.2.** An example of choppy movements present in the eye tracer. The image on the right is the frame that immediately follows the frame given by the image on the left. Note that this shows a movement from the right side of the eye to slightly left of the origin.

points, giving approximate position readings for each eye event. These positional data points were then translated onto a canvas using the aforementioned graphics library and played back to create a virtual simulation of the eye movements for a given dataset.

## 5.2 Commentary

The eye tracer does show some shortcomings of my classifier. First and foremost, the timelapse of eye movements oftentimes would look “choppy,” with the eye moving with seemingly erratic movements. An example of this can be seen in Figure 5.2, which shows two adjacent frames from a screen capture of the eye tracer. As can be seen in this figure, the eye moves incredibly quickly across the surface of the eye. It has not been definitively determined where exactly this issue is coming from, though it is likely due to the start and stop issues that were found with the hidden markov model. Smoothing of the video does help in reducing the conspicuousness of the movements from the perspective of viewers, but it does not tackle the core issue behind the choppiness.

Despite this issue, the eye tracer was capable of accurately modeling movements of the eyes via EOG data that was both classified and quantified by the realtime classi-

fication system. This shows the potential power and efficacy of the Jins Meme glasses and the realtime classifier, as it demonstrates the ability for the data to be applied in a concrete manner.

# Chapter 6

## Case Study: Activity Recognition

One of the more interesting potential applications for EOG is being able to differentiate between different activities via differences in the movement patterns of the eyes. It has been established previously that certain activities, especially something like reading, has very specific eye movement patterns [10, 56]. As a starting point for using the Jins Meme for activity recognition, I recorded myself performing three different activities: reading an article on my computer, watching highlights from a hockey game, and playing a video game (Super Meat Boy). I then analyzed the three datasets and attempted to build a set of features that differed between them and that could be used in a classification system.

### 6.1 Classification Accuracy

One observation that became quite apparent with the activity recognition data samples that were captured was the sheer complexity of eye movements during real activities versus the control datasets. While it may seem fairly obvious that movements of the eye are much more complicated than looking left, right, up, or down as in the control data, it was still rather interesting to see that even something as “simple” as reading incorporated a great variety of different eye movements, and it wasn’t quite as straightforward as a simple left-right pattern.



Perhaps as a result of this added complexity, the realtime classification system saw greatly reduced accuracy on the activity recognition datasets. As an example, the data from the reading task showed significantly more up/down movements rather than left/right movements, which, despite the aforementioned conglomeration of complex movements, still runs contrary to what one would expect a reading task to entail.

## 6.2 Features

From a high level, any given task involves moving the eyes in order to perceive important information in the current setting [56]. However, each different task and setting requires very different, specific movements. For example, when reading, the movements of the eye are concentrated on finding the next word to focus on, whereas hockey requires tracking a puck across the ice. These specific movements then lead to inherent differences in the eye movements that are present in different tasks. Given this, in order to quantify and classify different tasks, a set of features that describe the eye movements for a given time period can be identified. Since this work focuses primarily on directional movements of the eyes, features relating to the relationship between these movements were emphasized.

As can be seen in Table 6.1, which shows the raw results from the classifier on the activity data, even with rather noisy data, there are some clear differences between the different activities. The main differences that can be seen specifically in this table is the difference in the distribution of eye events. Thus, one of the first features to be added to the feature set was the normalized count of the events. To get these numbers, I simply divided the number of times each event occurred and divided this by the total number of events in the dataset. In addition to this, I added the time spent in each event to the feature set. While related to the count of the events, this differs slightly in that it gives more weight for events that may be very slow and time consuming, such as moving

**Table 6.1.** Numerical values for various features and parameters that were observed for the three studied activities: reading an article online, playing Super Meat Boy, and watching a hockey highlight reel.

<b>Dataset</b>	<b>Blinks</b>	<b>Left Movements</b>	<b>Right Movements</b>	<b>Up Movements</b>	<b>Down Movements</b>
Reading	30	5	4	20	12
Super Meat Boy	139	11	15	113	75
Hockey Highlights	53	11	10	64	49
	<b>Blink Percentage</b>	<b>Left Percentage</b>	<b>Right Percentage</b>	<b>Up Percentage</b>	<b>Down Percentage</b>
Reading	42.25%	7.04%	5.63%	28.17%	16.90%
Super Meat Boy	39.38%	3.12%	4.25%	32.01%	21.25%
Hockey Highlights	28.34%	5.88%	5.35%	34.22%	26.20%
	<b>Time Blinking</b>	<b>Time Left</b>	<b>Time Right</b>	<b>Time Up</b>	<b>Time Down</b>
Reading	3.63%	0.21%	0.15%	0.95%	0.75%
Super Meat Boy	3.31%	0.10%	0.18%	1.05%	1.39%
Hockey Highlights	3.64%	0.35%	0.25%	1.87%	2.58%
	<b>Avg Time Left</b>	<b>Avg Time Right</b>	<b>Avg Time Up</b>	<b>Avg Time Down</b>	<b>Fixation Length</b>
Reading	48.0 ms	37.5 ms	57.0 ms	86.0 ms	822.18 ms
Super Meat Boy	49.09 ms	70.03 ms	49.12 ms	127.6 ms	739.22 ms
Hockey Highlights	68.18 ms	45.0 ms	59.53 ms	131.02 ms	582.88 ms

across a line while reading.

Another set of features, which deviates a bit from the focus on movements and their relationships deals with the average length of saccades and fixations in the given dataset. This data is shown in Table 6.1, and demonstrates that tasks such as reading, which typically involves short movements from word to word across a line, generally has shorter lasting saccades than more intense tasks such as playing a game or watching a sport, which involve more constant, long-reaching movement of the eyes as the person scans the visual area.

The other main category of features that was added to the feature set are the transition matrices between different eye events, which are shown in Tables 6.2 - 6.4. By cultivating this, we are able to further distinguish between activities that happen to have very similar distributions of eye events, as it is unlikely that they will also have the same transition patterns between eye events. Specifically within the datasets obtained in this project, this would be particularly useful in differentiating the hockey and Super Meat Boy tasks, which were similar in terms of the previous features, but have significant differences that can be picked up from the transition matrix.

**Table 6.2.** Transition matrix for reading

	<b>Next Movement</b>				
	<b>Left</b>	<b>Right</b>	<b>Up</b>	<b>Down</b>	
<b>Previous Movement</b>	<b>Left</b>	2.44%	4.88%	4.88%	0%
	<b>Right</b>	0%	0%	7.32%	2.44%
	<b>Up</b>	9.76%	2.44%	17.07%	19.41%
	<b>Down</b>	0%	2.44%	17.07%	7.32%

**Table 6.3.** Transition matrix for playing a video game

	<b>Next Movement</b>				
	<b>Left</b>	<b>Right</b>	<b>Up</b>	<b>Down</b>	
<b>Previous Movement</b>	<b>Left</b>	0%	0%	3.74%	1.40%
	<b>Right</b>	0.47%	0.47%	3.27%	2.80%
	<b>Up</b>	4.21%	4.67%	22.89%	20.56%
	<b>Down</b>	0.47%	1.87%	22.89%	9.81%

**Table 6.4.** Transition matrix for hockey highlights

	<b>Next Movement</b>				
	<b>Left</b>	<b>Right</b>	<b>Up</b>	<b>Down</b>	
<b>Previous Movement</b>	<b>Left</b>	0%	1.49%	2.99%	2.99%
	<b>Right</b>	0.74%	0.75%	2.99%	2.99%
	<b>Up</b>	5.22%	2.99%	23.13%	16.41%
	<b>Down</b>	2.23%	2.23%	17.91%	14.18%

# Chapter 7

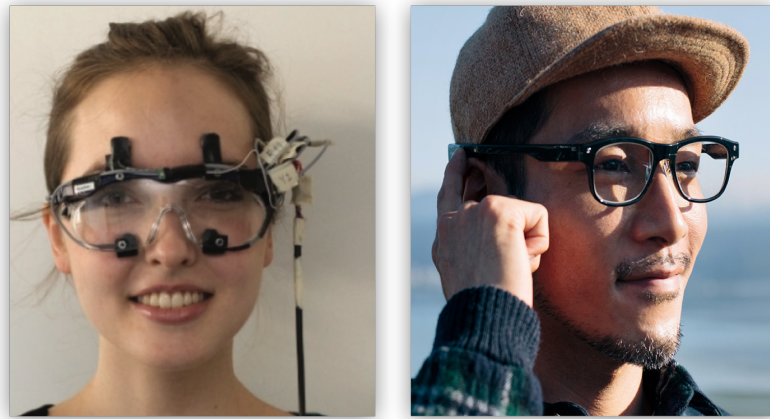
## Evaluation of EOG and the Jins Meme Glasses

In this thesis so far, I have introduced the Jins Meme glasses as a novel and intriguing EOG system that differs greatly from traditional EOG set ups. Additionally, I have described my work on a realtime classification system that is able to analyze EOG data in order to provide information about eye events that occur. With these experiences in mind, in this chapter, I provide a more in depth commentary on the strengths and weaknesses of EOG in general and the Jins Meme glasses.

### 7.1 EOG

One of the big questions I had coming into this project was whether or not EOG data was capable of being properly processed in realtime and if there was any meaningful data that could be extracted. As was seen in the data collected in this study, it is definitely possible to extract meaningful data from the eyes in realtime, though it may not be completely accurate. Looking forward, with more sophisticated algorithms and more in depth training datasets, it should be possible to model and detect higher order eye events, which could in turn lead to much more innovative applications for EOG data.

That said, even with a classifier that was not perfect, the two case studies in this



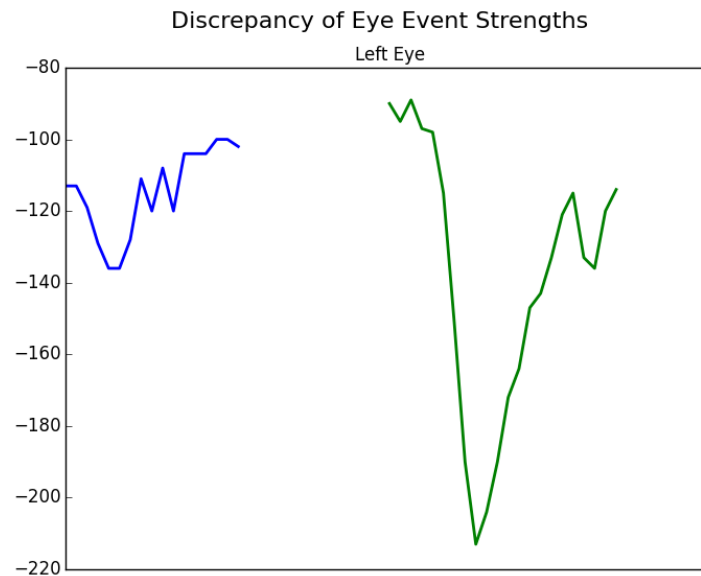
**Figure 7.1.** A comparison of the EOG setup used in [7] (on the left) and the Jins Meme glasses (on the right *from* [39]).

thesis showed that there still definitely are applications for eye data; in this case modeling activities and being able to track an eye. In my opinion, this is an exciting development that lends itself well to further research which can refine and optimize the methods in this work so as to find even more applications for EOG data.

## 7.2 Jins Meme Glasses

The Jins Meme glasses were a very interesting EOG system. As opposed to more traditional, historically used, and accepted EOG platforms, the Jins Meme glasses choose to be somewhat minimalistic in their approach to EOG. Whereas most systems have upwards of 6-8 electrodes and a ground node, the Jins Meme glasses have only two and a ground node. By doing this, the Jins Meme glasses are able to maintain a rather unassuming profile when compared to other EOG systems. This discrepancy in appearance can be seen in Figure 7.1, which shows that the glasses really could be worn as an everyday accessory as opposed to other EOG systems.

I previously discussed some issues with the Jins Meme glasses, such as the electrode placement of the glasses only capturing lateral movements and the nature of



**Figure 7.2.** An example of a small left eye movement event on the left in blue compared to a more typical movement on the right in green.

them being glasses leading to constant repositioning or slipping. All that considered, though, the glasses fared much better than I was expecting them to. While I did have some trouble with vertical movements, and there definitely was noise in the data causing a fair amount of false positives, at the end of the day, I was able to fairly accurately identify movements of the eye.

That said, however, I do worry about the applications of the glasses for more complex and sophisticated applications for two main reasons. First, as was seen in the second case study, eye movements are very complex, and without proper modeling of vertical movements of the eye, I do think it will be difficult for the Jins Meme glasses to be of much use. Perhaps the stop-gap solution of detecting vertical events may be enough to provide some amount of utility in this scenario, though. Beyond that, though, I do think the glasses at some point will require some sort of vertical electrode in order to properly model most complex eye events.



The second issue I see with the Jins Meme glasses is the sensitivity of the electrodes. I did notice at times that some eye events showed up as very minuscule maxima or minima in the data. A few examples of these are shown in Figure 7.2, with some more “typical” events as a comparison. I was able to determine that the small hills and valleys were not the result of slower or smaller movements of the eye, which leads me to believe it is likely the glasses not being sensitive enough to properly pick up the electrical signals that come with the movements with enough clarity to differentiate them from background noise. Unfortunately, it is unclear at this time, though, if this is something that can readily be fixed with more sensitive equipment, or if a pair of eyeglasses simply are not equipped for the job.

# Chapter 8

## Future Work

Although the work presents a realtime classification system that works well with the Jins Meme glasses, there are several potential avenues for future work.

### 8.1 Jins Meme Data

One area of the glasses I did not look into much in this thesis was the presence of an accelerometer and gyroscope in the glasses, which seem to be the source for most of the Meme applications built by Jins [38]. An interesting category of activities that I think would be very interesting to add to the second case study are non-computer based activities, such as interacting with items on a desk, speaking to others, or even zoning out and staring at the wall. All of these could potentially be modeled by a combination of the accelerometer and gyroscope data, which I believe should work symbiotically with the EOG data.

### 8.2 Realtime Classifier System

While I was fairly happy with the realtime classifier and its performance on the control datasets, there still is much that can be done in order to improve it, both from a performance perspective and an accuracy perspective. From the performance viewpoint,

the classifier is written currently in a fairly high-level programming language, Python, and makes generous use of libraries and other unoptimized pieces of code. By both optimizing the codebase and perhaps moving it to a different language, significant headway could be made in allowing the classifier to run. Porting the system to a language like Java, for example, could show significant performance improvements due to optimizations that can be made at run time by the Java Virtual Machine's high performance JIT compiler.

### **8.3 Hidden Markov Model**

While the hidden markov model that is in use by the classifier currently has shown fairly consistent and reliable results, it was chosen fairly arbitrarily and did not go through a rigorous testing process in order to ascertain that it was indeed the best system for the job. I would argue that a hidden markov model of some sort is the correct tool for the event detection job, but it is possible that other hidden markov models, such as one based on a multinomial distribution, could lead to better results.

Beyond the type of model, though, even the model that is in use right now still suffers from some amount of unreliability in detecting the start and end of an event. Thus, adding extra features to the model, or perhaps investigating different ways of training the model, could lead to improvements in the performance of the model.

### **8.4 Eye Event Classification**

The event classification system in place at the moment is actually fairly distantly removed from modern accepted data mining and machine learning techniques. While it did seem to perform the job on the control datasets, I have little doubt that the current system will not scale to higher order eye events. As such, a new event classifier based on a more prominent classification technique, such as a Support Vector Machine, is due to be built.

## **8.5 Dataset Collection**

One of the largest shortcomings of this project was lack of access to a large supply of datasets. For future work in EOG data mining, I think it is quite important for more time and effort to be placed in collecting and labelling datasets to be used as both training and testing material. With a larger corpus of datasets that includes recordings from multiple individuals, it will be significantly easier to build and test data mining systems, while also allowing the systems to perhaps be more meaningful, as they across a larger set of data.

## **8.6 Next Steps**

Apart from tuning the realtime classification system, there additionally exists a large amount of work to be done in order to better understand the eyes and the trends they exhibit. Toward this end, I would propose two main avenues of future work. The first is to perform a larger scale study comparing the strengths and weaknesses of various EOG apparatuses. This would allow for design decisions for EOG systems to be better understood and would potentially allow for more realistic use cases of EOG to be identified. The second avenue would involve analyzing the EOG data in a way that allows for more “classical” eye-tracking measures, such as degree-based movements and saccade/fixation relationships, to be observed. This would allow for the EOG data to be verified as consistent with other work, and would also allow for a larger body of related work to be accessed.

# Chapter 9

## Conclusion

Despite electrooculographic technology existing for quite a while, uses for EOG have been limited and have primarily been experimental in nature. Additionally, most applications for EOG have been limited to the medical field, where it has potential applications in sleep studies, child development, and other areas. That said, with the dawn of new technologies such as virtual and augmented reality, EOG has very real applications within the realm of human-computer interaction. In fact, I do believe that, at some point in the future, EOG will actively be used by VR and AR systems as an input modality in some capacity.

In this project, I set out to analyze the efficacy of using EOG in real life settings, with the hopes of showcasing EOG as a potentially viable future input modality for interaction with computers. The project demonstrated a two-part classification system incorporating a hidden markov model and classifier that was able to classify directional eye events and blinks with an accuracy of 89.7%, all while using a fairly simple and non-exhaustive EOG system. Additionally, the work in this thesis also shows that there are readily available use cases for EOG technology that could potentially have real world significance for either upcoming pieces of technology or applications.

Several new pieces of technology that have become prevalent in recent years revolve around the concept of finding a new input modality. It is my belief that the eyes

are perhaps the most intriguing, powerful, and largely untapped input sources we as humans have to offer, outside from the brain itself. With this in mind, I have high hopes for the future of electrooculography as a future direction for the world's technological interaction infrastructure.

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