Using EEG Noise as a Means for Adding Robustness to Eye Gaze Interfaces

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Abstract

Following in the footsteps of Shwetak Patel (University of Washington), we take a your noise is my signal approach to the Midas Touch problem. Historically, the Midas Touch problem has been an issue with eye gaze interfaces because input from eyes cannot be turned off. Additionally, throughout the history of the use of EEG, there has been significant research in the removal of artifacting introduced by the EOG and EMG signals. Using an off-the-shelf Bluetooth-enabled EEG system, we use the noise introduced by eye and muscle movements in the face to determine whether inputs to an eye-tracker system are intentional or unintentional. We utilize existing signal processing methods to separate out muscle activity and eye activity from the EEG signal and from those signals we can visually discern intentional and unintentional blinks. Using Support Vector Machines (SVM), we classify intentional and unintentional blinks.

Keywords: EEG, EMG, EOG, Midas Touch Problem, Human-Computer Interactions (HCI)

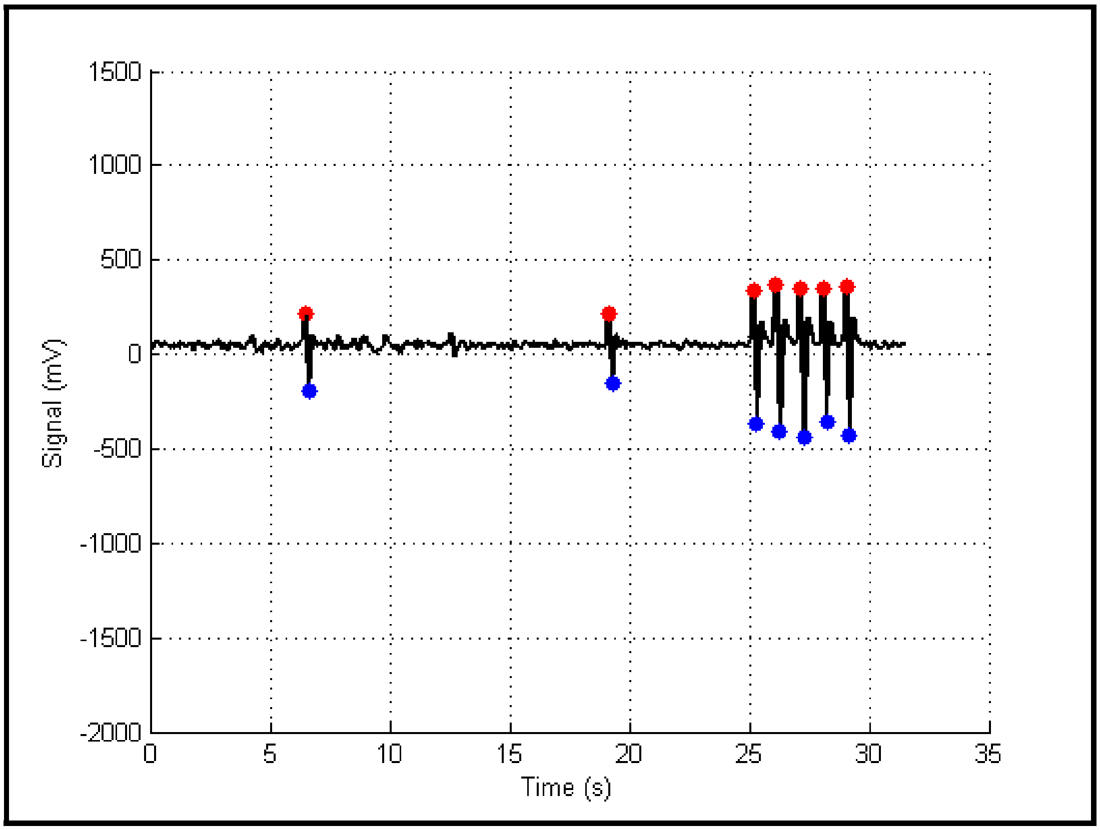

Fig. 1. Graphical representation of unintentional versus intentional blinks using the EOG signal extracted from EEG noise. Participant was asked to look ahead for 25 seconds. At the end of the 25 seconds, participant was asked to make 5 sequential blinks.

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I. Introduction

A. Problem Statement

The Midas Touch problem has plagued eye gaze interfaces because the eyes cannot be turned off. One of the main challenges when using eye gaze interfaces for selection purposes, such as moving a mouse, is to be able to add a system that allows the user to engage or disengage the eye gaze interface. However, a good system should be quick to operate, not increase the cognitive load unnecessarily, and not disturb the users gaze-pattern. Thus, in order to develop a robust eye gaze interface, a secondary system is required to either engage/disengage or confirm selection modes. We aim to implement an EEG-based secondary system to confirm selection by determining whether the user is in an attentive mode. .

B. Motivation

With the introduction of Google Glass, there has been a reemergence of developing touch-less interfaces. Previously speaking, implementation of hands-free interfaces typically use voice prompts. Motorola has developed devices that use an always-on voice recognition system to perform queries or simple tasks, such as sending text messages. However, when these devices go out in the wild such as Google Glass or the Moto X, the effectiveness of voice prompts diminish, whether it be through social inappropriateness or through unideal conditions, such as ambient noise or unintentionally picking up active conversations.

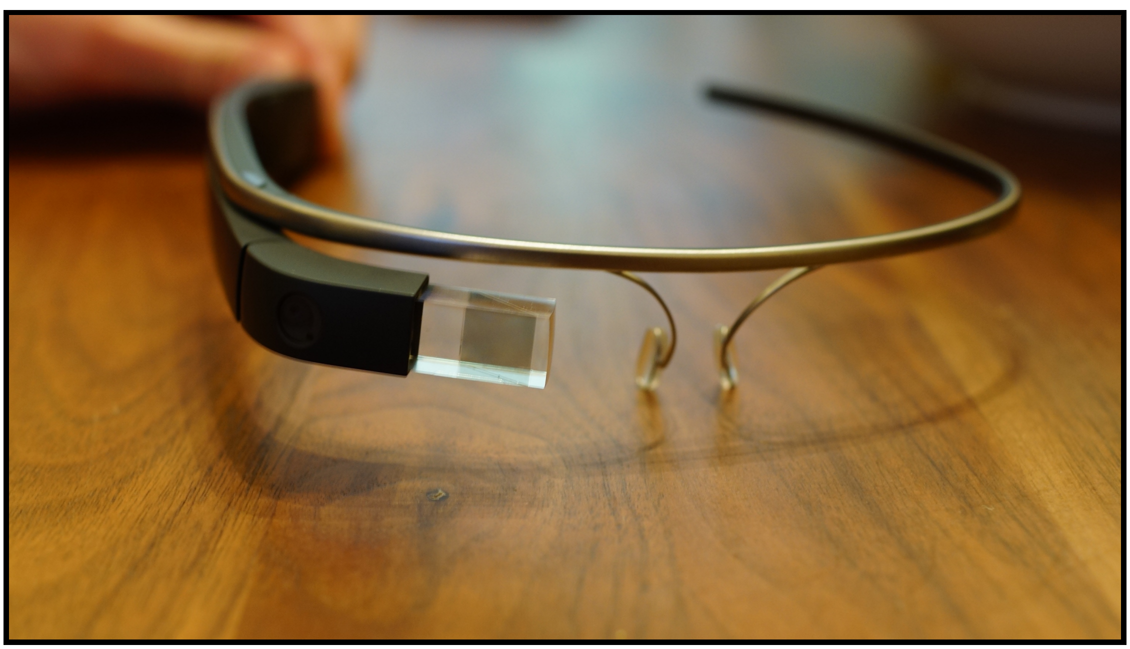

Fig. 2. Google Glass provides a heads-display to users so that they can read emails and message and perform other smartphone-like functions. Image Courtesy: Wikipedia

In conditions where it is socially unacceptable to perform voice commands, such as while attending class, a touch-less EEG-based interface would allow the user to perform commands

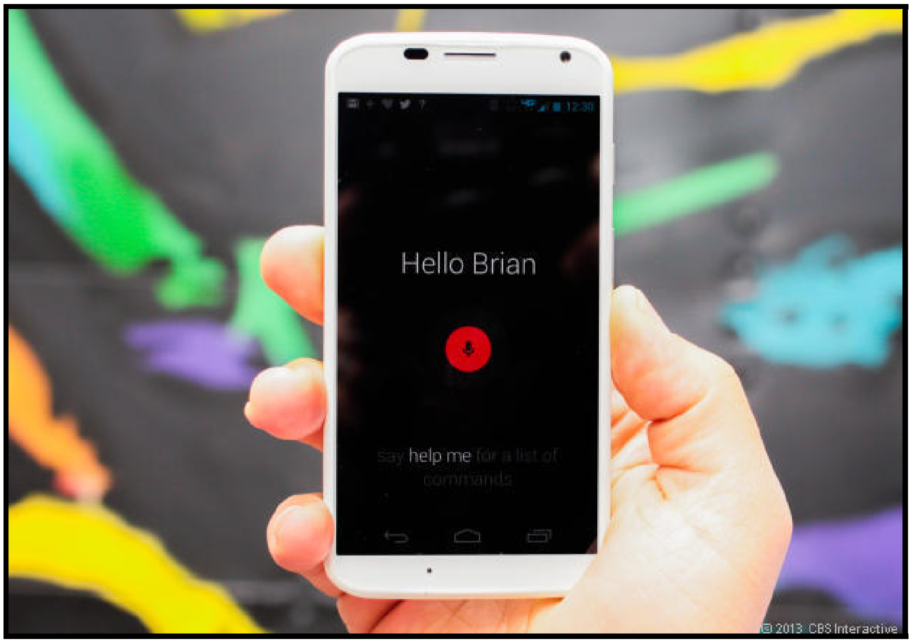

Fig. 3. The Moto X contains personalized voice recognition that is always-on and always listening. Image Courtesy: CNET

on a heads-up display without interrupting or disturbing those around him/her. Furthermore, such an interface would allow the user to avoid voice miscues based on the ambient noise of the classroom. For instance, in the presence of active conversation, an always-on EEG interface would localize prompts to the user better than an always-on voice system that may pick up other people speaking. Additionally, specifically tailored to Google Glass, a touch-less interface would allow users to avoid using the touchpad on the side of the device. For a heads-up display to be truly useful, the complete functionality of the device should be available without the requirement to touch it. Since the device needs to be touched in order to activate its functionality, such as turning it on, waking it from sleep, taking pictures, and even selecting simple options, it only offers a marginal functionality increase over touch-based devices such as smartphones or tablets.

C. Related Work

There are a few interesting, relevant developments in the Human-Computer Interfaces (HCI) field that fall within the scope of our research. These state of the art inputs present methods to control computer interfaces without the use of a direct input, such as a mouse, keyboard, or touchscreen.

1) Skinput:

Skinput is a technology co-developed by the HCI Institute at Carnegie Mellon University and Microsoft Research Labs. Skinput uses the human body as an acoustic source which permits the skin to be used as an input surface. [1] By analyzing the vibrations that propagate through the body upon the tapping of fingers, they are able to provide an always-on input system. However,

Fig. 4. The Skinput uses an armband to collect its acoustic input. Image Courtesy: Microsoft Research

one of the limitations of the Skinput system is that it still requires tapping or touching. For instance, a user would need to tap a table, a wall, or their own body in order to make an input. Since we desire a device that promotes functionality without the requirement of touch as a basis of interfacing, the Skinput falls short.

2) EMG Control:

The next interface we looked at was a Muscle-Computer Interface developed by the University of Washington, Microsoft Research Labs, and the University of Toronto. The system uses Electromyography (EMG) in order to classify finger gestures as a method of producing an always-on input. [2]The team developed six different grasps (spherical, cylindrical, palmar, tip, lateral, and hook), which allowed them to control a portable music device.

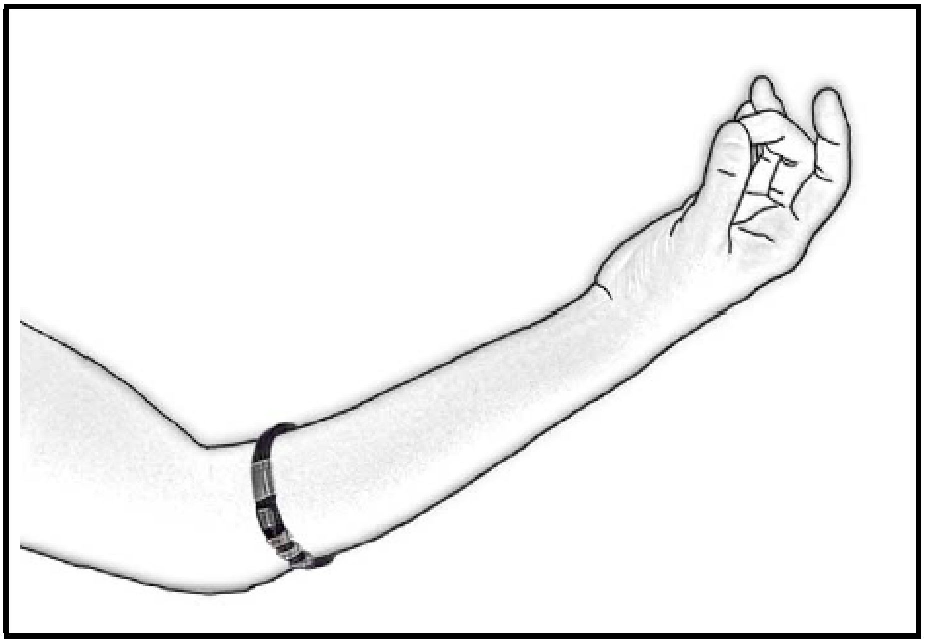

Fig. 5. This is an artist's rendering of the armband that would be used to collect EMG signals. Image Courtesy: Microsoft Research

However, one of the limitations of this system, as discussed in the paper, comes from this system developing its own ”Midas Touch” like issues. Scenarios, such as carrying groceries, may engage the system by triggering one of the classifications (hook in this case) and would provide a miscue to the device receiving input from this system. Since we desire a device that is robust to these unintentional inputs, the EMG method falls short.

3) Microsoft Kinect Methods:

We also looked at popular human-computer interfaces developed via the Microsoft Kinect hardware. Particularly, we looked at the Kinect Mouse Cursor project that allows users to use hand gestures as a mouse input. [3]. Specifically, the method detects hands with the Kinect hardware and movement is measured along the x and y axes. The right hand moves the cursor and the detection of a left hand constitutes a click.

However, the current implementation does not use hand geometry or finger detection for added functionality, such as rotate or middle click. Right click, for instance, has not been implemented. Additionally, although functionally any camera could be used to detect hands, this system requires a user's hands to be always in the field of view of the camera to be considered ”always-on”.

4) Functional Near-Infrared Spectroscopy:

Lastly, we looked at the fNIRS HCI system developed by Tufts University. fNIRS measures changes in blood oxygenation, which can be then used to determine spatial brain activity.[4] The main argument for fNIRS HCI is that the signal is robust and is relatively unaffected by

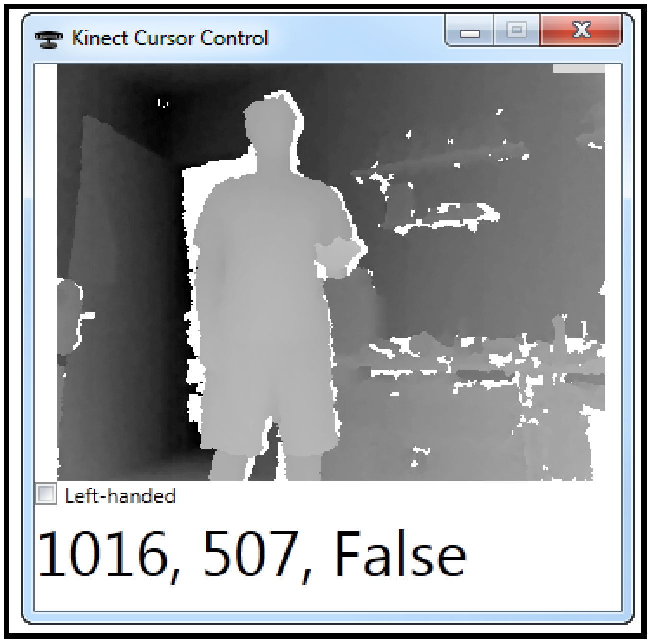

Fig. 6. This is a screenshot of the Kinect Cursor Control interface. Image Courtesy: Kinect Mouse

non-mental activities, such as blinking. The main application presented by this method of HCI was ”The Stockbroker Scenario”. In this case, a stock broker is bombarded with information, and the fNIRS interface is used to determine the mental workload on the person to then modify the presentation of information to the person to decrease the workload as necessary.

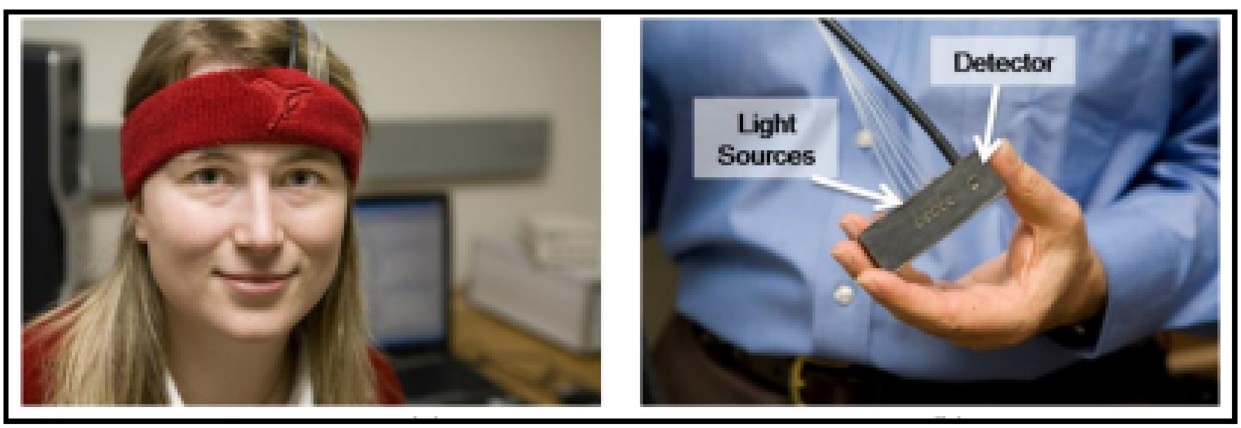

Fig. 7. This image shows the particpant wearing the fNIRS device in a headband alongside an image showing the actual device. Image Courtesy: Tufts University

However, it seems that fNIRS is a sensory interface rather than an input interface. fNIRS focuses more on determining the state of a user rather than acquiring an input. For that case, it seems that fNIRS would fall short as an input method, but may prove to be useful in developing a ”clutch” for an eye-based interface by tracking user attentiveness. It is important to quickly note that fNIRS does not discriminate against the source of mental workload.

D. Potential Users

1) Users who cannot perform motor functions:

An immediate use-case for a system described in the Introduction would be those who have paralysis and cannot use methods that require neuromotor control. In these cases, the Skinput, the EMG, and the Kinect systems all fail to provide an adequate human-computer interface. Although an fNIRS-based system may provide an alert that the user desires an action to be completed, it alone does not provide a *command* input.

2) Users who wish to perform functions in secret:

Additionally, as described above in the Motivation, there are a myriad of situations in which a user would enjoy a hands-free and discreet human-computer interface. In the case of interfacing with Google Glass, it would be socially advantageous to be able to control the device without the use of your hands. Since the device is already incredibly conspicuous sitting on the user's face, it attracts noticeable attention to the user. While those who have typical smartphones may be able to check emails, send text messages, or even snap a quick picture, in secret, a Glass user may not be able to perform those functions in secret without the use of a hands-free interface. With an EEG based solution, it may be possible to perform actions that only the user will know.

3) Users who cannot use their hands during a task:

Another use case is the increasing use of mobile technology while driving. With the increasing capabilities of smartphones, more and more drivers are distracted by using their smartphones through standard interfaces. 10 states prohibit hand-held cell phone use while driving, but no state prohibits all cell phone use. As a result, smartphone software companies, such as Google (Android) and Apple (iOS) have developed products such as Google Now and Siri to allow for hands-free interfacing with their products. However, often times, these voice-based products either create more of a distraction to the driver or do not have sufficient integration into the applications they control. For instance, if I ask either product to ”Navigate to Harvard”, I receive one of the following options:

- *Misinterpretation:* ”Navigating to Habor”. In this scenario, the voice-based interface misunderstood my request for ”Harvard” as ”Harbor”. Typically, a user will have to use the touch interface of the device to exit out of that request and reissue another request.
- *Multiple Chocies:* ”Here is a list of Harvards close to you”. In this scenario, the voice-based interface presents a list of choices, in which the user will have to select from via the touch interface.
- *Insufficient Integration:* ”Found Harvard. Shall I begin navigation?” In this scenario, the voice-based interface finds the correct choice, but rather than immediately starting navigation, it presents an onscreen button for the user to press in order to begin navigation.

In all of the above situations, although I make an attempt to perform hands-free navigation, there is a return to the touch-interface to complete or stop an action. With an EEG based solution, a user could address all three usage scenarios without having to use the touch-interface of the smartphone.

II. Design Goals

The main design goal of this project was to use an EEG-based method as a means to add robustness to typical eye-gaze interfaces. As mentioned in the Problem Statement, many eye-gaze interfaces suffer from the inability to determine whether an eye movement came as a result of the user making a voluntary movement as input versus the user making natural involuntary movements irrelevant to the human-computer interface. An immediate field of improvement would be improving the accuracy of blink-detection in order to provide a robust method for selection. In addition, we look to see if an EEG-based method can improve the (x,y) coordinate system used in many eye-gaze interfaces.

Thus, the goal of this project should come in its ability to separate voluntary movements from involuntary movements. We employ the following quantitative goals to direct this project:

A. *Voluntary Blink Detection Accuracy*

A primary goal is to accurately determine voluntary blinks for the purpose of making selections. We define a voluntary blink to be a blink that is made for the sole purpose of making a selection within a computer interface, such as making a click. We assert that an 80% accuracy is a good baseline as a method for determining a successful system.

B. *Involuntary Blink Detection Accuracy*

A complementary goal is to accurately determine involuntary blinks for the purpose of reducing false-positive selections. We define an involuntary blink to be a blink that is not made for the sole purpose of making a selection within a computer interface, such as natural blinks to clear dust. We assert that an 80% accuracy is a good baseline as a method for determining a successful system.

C. *Voluntary Eye-movement Detection Accuracy*

A secondary goal is to accurately determine voluntary eye movements for the purpose of switching selections or moving a cursor. We define a voluntary movement as one made for the sole purpose of such an action. Similar to our blink accuracy, we assert that an 80% accuracy is a good baseline.

D. *Involuntary Eye-movement Detection Accuracy*

A complementary goal is to accurately determine involuntary eye movements for the purpose of reducing false-positive movements. We define an involuntary movement as one that is not made for the purpose of input, such as a saccade. We assert that an 80% accuracy is a good baseline.

TABLE I
THE FOLLOWING TABLE SHOWS A LIST OF CRITERIA WHICH MEETING THE TARGET WOULD DEEM THIS PROJECT A SUCCESS.

Criteria	Target
Accuracy of voluntary blink detection	$\geq$ 80%
Accuracy of involuntary blink detection	$\geq$ 80%
Accuracy of voluntary eye-movement detection	$\geq$ 80%
Accuracy of involuntary eye-movement blink detection	$\geq$ 80%

III. DESIGN APPROACH

A. *Data Acquisition*

When we began this project, we required an economical EEG device that would also be relatively mobile. Typical laboratory grade EEG monitors cost on the order of tens of thousands of dollars and use head caps in which the participant's is doused with electrolytic solution prior to putting them on. We decided on evaluating two devices that were in the \$100-\$300 range that were also relatively uninvasive: the Neurosky MindWave Mobile and the Olimex OpenEEG Device.

1) Neurosky MindWave Mobile:

The Neurosky MindWave Mobile is the second generation MindWave device, adding Bluetooth v2.1 connectivity to the first generation MindWave device. The device has one active electrode at a fixed position on the forehead and supports sampling up to 512Hz. Lastly, the device is powered off a single AAA battery and is available for \$130 off Amazon.

On the Neurosky website, the device is stated to have direct compatibility with MatLab, but the documentation was slim (see "Significant Challenges and Pitfalls"). Fortunately, the device is supported by an open-source brain-computer interface called OpenVibe, which allowed us to receive the raw signal output from the device.

The device does provide a very low noise profile, most likely aided by its power source being local to the device rather than from a power main. Additionally, the 512Hz sampling helped prevent aliasing of high-frequency signals. Lastly, since the device's connectivity is via Bluetooth, a user is not necessarily physically tethered to a computer: they are able to walk around while data is being recorded.

2) Olimex OpenEEG Device:

The second device we looked into was the Olimex OpenEEG Device. Originally, the OpenVibe platform was co-developed with the OpenEEG hardware platform and the OpenEEG is still the recommended device by Inria, the developers of OpenVibe. The device features configurations of either 4 active and 1 passive or 5 passive electrodes, a 256Hz sampling frequency, and the electrodes can be placed to the user's choosing. However, the electrodes do require electrolytic gel and adhesive tape to secure. Unfortunately, this cause a level of discomfort among the participants. Additionally, the device's connectivity and power is via USB 2.0, so the device

Fig. 8. This image shows a user wearing the Mindwave. Image Courtesy: engadget

must be plugged into a computer. The device can be purchased for about $195 for a device and 4 active, 1 passive electrodes.

As stated earlier, the device is fully supported by OpenVibe, but also has support for other third-party visualiation software. Although the device features 5 electrodes, one of the electrodes must be dedicated to ground and two of the electrodes must be connected as pairs, thus resulting in a maximum of two channels as input.

Unfortunately, the device suffers from a significantly high noise profile sourced most likely from its USB connectivity (see ”Significant Challenges and Pitfalls”). In addition, the device's 256Hz sampling frequency seems to cause some aliasing in which blink artifacts that appear in the MindWave Mobile do not show up in the Olimex OpenEEG.

B. EEG-Based Approaches

In this project, in order to determine intentional versus unintentional blinks, we looked into approaches that would provide a quantifiable difference from EEG signals. The approaches we evaluated were Event-Related Potentials (ERP), Frequency Tagging, and EEG Noise approaches.

1) ERP Approach:

The first approach we evaluated was to look for various Event-Related Potentials (ERP) that could possibly confirm a blink as intentional as a response to a positive stimulus. Specifically, we were interested in the P200 and the P300 waveforms. These two waveforms typically peak at about 200ms and 300ms after the onset of external stimuli for the P200 and P300, respectively.

Fig. 9. This is an image of the Olimex OpenEEG. Note that the electrodes do not have ”pads” so they require electrode gel to make contact. Image Courtesy: Olimex

Ideally, when a user is presented with an option or a selection, this would act as the external stimuli in which the user responds with a blink.

However, unfortunately, our device was not sensitive enough to detect ERPs. The P200 is approximately +3 μV off the baseline voltage and the P300 is approximately +6 μV. Typically, these waveforms are recorded by running multiple time-locked trials from the onset of the stimulus. The recordings are averaged together to finally see the apparent waveform. Thus, we decided to abandon this approach in favor of other methods.

2) Frequency Tagging Aproach:

The second approach we evaluated was to use a frequency tagging approach. Frequency tagging is a method in which a watermark signal, such as a pulsating light source at a fixed frequency, is injected into the visual stimuli presented to the user which can then be picked up in the EEG signal. This method has been previously used to determine selective attention by Radbound University in the Netherlands.[5]

This method on the surface appeared to be a good place to start, as we can easily develop a system that injects a watermark after a blink to confirm the user's attention. However, after having a participant watch a video of pulsating light at 4Hz, I was unable to see a clean waveform of 4Hz on either the MindWave or the Olimex. As a result, we decided to abandon this approach.

3) EEG Noise Approach:

The third approach we evaluated came as a result of a happy accident. When using the

MindWave, I noticed that I could create spindles by clenching my jaw or clenching my fist near the electrode. In addition, I noticed that the action potential artifacts from the eye muscles in the waveform appeared to be different for intentional and unintentional blinks.

Taking a ”Your Noise is my Signal” approach, I decided to use parts of the EEG signal that are traditionally considered to be noise and are extracted out as a way to determine intentional vs unintentional blinks. Specifically, I decided to keep the signal artifacts sourced from the eye muscles and facial muscles and I noticed, at first visually, that I should be able produce two separate signals, one comprised of action potentials and the other comprised of spindles.

C. *Data Processing Approaches*

In choosing the noise-signal approach, there is a significant amount of signal processing that is required before we arrive to a quantitatively *useful* signal. We begin by producing two identical data streams, one destined to become an extracted EMG signal, the other an EOG signal. The data processing for these experiments were completed in two parts: via the OpenVibe Designer Studio and MatLab. The OpenVibe Design Studio is configured to acquire data from the OpenVibe Acquisition Server along port 1024. Once the data is loaded into the Design Studio, we use functional elements within the system called ”Boxes” to perform some basic pre-processing. We split the data stream into two separate streams.

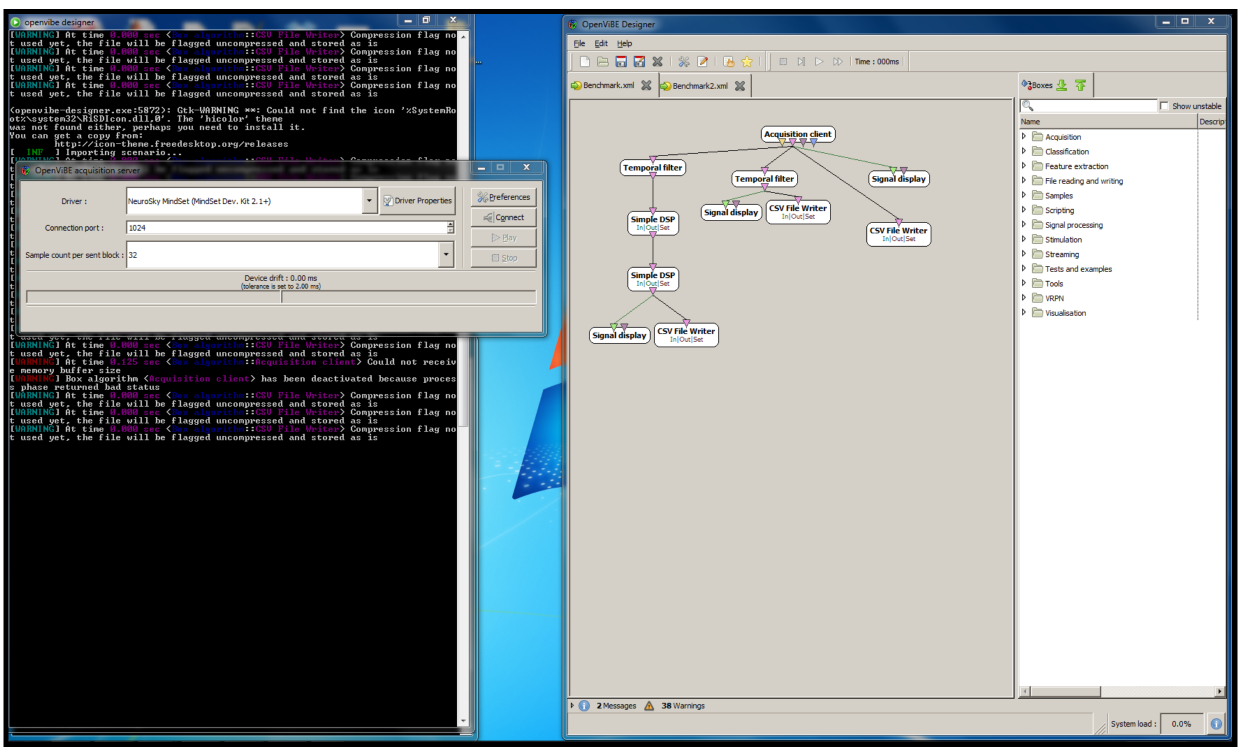

Fig. 10. This image shows a typical OpenVibe configuration with the Acquisition Server GUI on the left and the Design Studio with Boxes on the right.

1) Fourier Analysis:

Within the OpenVibe Design Studio, we perform Fourier analysis and apply a bandpass temporal filter with a low cut off frequency of 38Hz and a high cut off frequency of 46Hz. This filter allows us to extract the EMG signal from the EEG signal. We then perform the following function on the data where f(x) is the output and x is the input:

$$f(x) = log(1 + x^2)$$

We first square the data in order to amplify changes in amplitude and remove all negative values from the dataset. We then we add 1 in order to ensure there are no values of zero in the data set and take the log to normalize. This transform allows us to convert spindles into peaks. We then output the data to a CSV file.

Similarly, we perform another Fourier analysis simultaneously and apply a lowpass temporal filter with a high cut off frequency of 4Hz. This filter allows us to extract the EOG signal from the EEG signal. We then output the data to a CSV file separate from the one mentioned above.

2) Feature Quantification and SVM:

With regards to developing a blink classifier, we use MatLab to detect local minima and maxima (with some rudimentary thresholding and selectivity) within the EOG data. After determining the local minima and maxima, we can determine the total amplitude of a blink. We then collect the amplitudes of the blinks and use a support vector machine to develop a threshold in which we separate the blinks into two categories. Additionally, we also look at the time constant between the local maxima and minima, which we then collect for each blink and use another support vector machine to develop a separate threshold to separate the blinks into two categories. We also noticed, from looking directly at the data, that intentional blinks have a maxima, minima, maxima pattern and unintentional blinks have a maxima, minima pattern. This is another distinction that we can use to classify the blinks.

During the same time the EOG data is being processed, we process the EMG data to see if there is a similar response for unintentional and intentional blinks. We use a similar script to process the EMG data and we noticed that unintentional blinks do not evoke an EMG response. However, for intentional blinks, the EMG response produces distinct peaks that can be picked up by our peak finder. Thus, we deduce that an EMG response is closely linked to intentional blinks.Through these three methods, we should be able to build a robust system for blink detection.

D. Human-Computer Interfacing

1) Blink-based slection:

One of the features we can enable as a result of our blink detection is a robust blink-based selection. Within MatLab, we can enable Windows commands, such as right click. Upon the detection of an intentional blink, we are able to make right clicks. The system ignores involuntary blinks.

2) Cartesian cursor control:

One of the features we can enable as a result of eye movement direction detection is to develop an (x,y) coordinate system to move a cursor in the Windows (or other OS) environment. Ideally, we should be able to detect wave forms that correspond to the eye moving in the four primary directions. In the case that we cannot detect specific directionality with the EEG devices we have, we should be able to detect voluntary movements. In conjunction with eye-tracking devices, we should be able to produce a robust cursor control system. Please see ”Future Work”.

3) Custom macro development:

One of the more popular devices coming out of Kickstarter is the pressy, a single action button that utilizes the headphone jack to present commands to the smartphone. The button only produces a binary output, it does not have sensitivity to the pressure profile of a button press. In combination with the pressy software, they are able to produce macros that rely on single, double, triple, and quadruple clicks.

Fig. 11. Pressy is a single button that fits in the headphone jack of most smartphones. It is a single button that is paired with macros to provide additional functionality. Image Courtesy: Kickstarter

With the EEG-based voluntary blink detection, we are able to produce similar macros for other computing environments. For instance, two consecutive blinks can send a double click command to Windows. Three consecutive blinks can provide a right click. Four consecutive blinks can send the shutdown signal. With an EEG-based solution, we are able to develop new usage scenarios in addition to the typical selection schemes.

IV. Design Details

A. Participants

Two Caucasian males, aged 22, and one Asian female, aged 20, volunteered to participate in the experiment. Participants are daily computer users. No skin allegeies, irritation, or discomfort was reported when using the Neurosky MindWave Mobile. Discomfort in the form of ”stickiness” was reported when using electrode gel with the Olimex OpenEEG. None of the participants have had a history of facial paralysis.

B. Equipment and Setup

1) Data Acquisition Devices:

Data acquisition for these experiments was done by a Neurosky MindWave Mobile. The MindWave Mobile's active electrode was wiped before each trial to ensure proper contact. Participants were asked to use a moistened paper towel to clean their forehead prior to wearing the device. A 1.5V AAA lithium-ion battery was used to power the device. The battery was checked prior to each experiment trial to ensure the device provides proper readings.

2) Data Acquisition Software:

Data acquisition for these experiments was done via the OpenVibe platform. The OpenVibe Acquisition Server was configured to use the Neurosky Mindwave Mobile via Bluetooth and the device was set to a sampling rate of 512Hz. The Acquisition Server was also configured to include a 2ms drift correction.

3) Data Processing Software:

The data processing was done in both the OpenVibe 16.2 Design Studio and MatLab 2013b 64-bit. OpenVibe 16.2 needed to be run in compatibility mode within Windows 7 64-bit in order to run properly.

4) Data Processing Hardware:

Data processing was performed on a Lenovo ThinkPad W520 running Windows 7 64-bit equipped with a Quad-core Intel Core i7, 8GB of DDR3 RAM, and a 128GB SSD. CPU utilization was primarily single-threaded and required 100% utilization of a single core while using both OpenVibe Design Studio and MatLab. Memory usage hovered around 0.4GB during acquisition and processing. Hard-disk utilization was around 400KB for 35 seconds of data recording per stream.

V. Prototyping Narrative

A. Significant Challenges and Pitfalls

1) Neurosky MindWave Mobile MatLab Compatibility :

A fairly significant challenge arose when attempting to connect the Neurosky MindWave Mobile to MatLab. At first, it seemed to only require a simple serial port connection that would allow us to load the data in packet by packet. However, each packet seemed to be unreadable. Unfortunately, the documentation is fairly scarce and when contacting the manufacturer, Neurosky, for support on how to interface the device to MatLab, we were simply referred to sales in order to purchase their $700 ”developer package”. The third-party documentation we did end up finding required using an older, 32-bit version of MatLab on a 32-bit Windows operating system. In addition, it required a very ”hacky” .dll file that MatLab would be required to call in order to process the data. In the end, we decided to pursue other options when we discovered the OpenVibe platform.

2) Data Acquisition Hardware Failures:

During the course of this semester, the Neurosky MindWave Mobile was replaced twice due to hardware failures. Additionally, it seems that between headset to headset, there are inconsistencies in the noise profile. For example, in the OpenVibe Acquisition Server, the console will provide a rudimentary noise profile polled at one second intervals. For our second headset, we could not get the headset to have a noise profile of less than 12.5%, what the OpenVibe considers acceptable.

3) Data Acquisition Hardware Shortcomings:

One of the main challenges in developing a system that can perform both blink detection and eye-gaze detection is having hardware that is adequately sensitive and multi-channel. The Neurosky Mindwave Mobile only contains one channel, which hampers the ability to determine the orientation of the eye. On the other hand, although the Olimex OpenEEG is multi-channel, the device’s noise profile, integrated high-pass filter, and 256Hz sampling rate masks subtle artifacts in the EEG data. Much of the noise of the Olimex OpenEEG is exists in the 40-60Hz frequency domain, the same domain in which much of our EMG signal is sourced from. Lastly, the integrated high-pass filter seems to remove much of the EOG signal we use for blink detection.

4) OpenVibe Proprietary Data Streams (LuaSockets):

In order to produce an HCI that performs actions outside of the OpenVibe platform, we needed a way to push the data out of the OpenVibe ecosystem. However, the community-directed solution involves using an add-on called LuaSockets. I was unable to configure LuaSockets to provide a data stream into MatLab. Additionally, the other data stream that was recommended was a system called VRPD, which I was also unable to configure to work properly with MatLab. In the end, we opted for a solution that read portions of a CSV file output every 64 rows.

VI. Evaluation and Verification

A. Experiments and Results

In order to determine how accurate our system is, we devised two types of experiments:

1) Test 1: Voluntary versus Involuntary Blinks:

The first type of experiment, called Test 1, was an experiment geared to provide data in determining voluntary versus involuntary blinks. The participants were asked to look forward towards a computer screen for 25 seconds. Participants were asked to not withhold involuntary blinks. Blinks during this time frame were counted manually by the test administrator. After the 25 second period, participants were asked to continue looking forward and commence 5 voluntary blinks as if they were intended for making a selection.

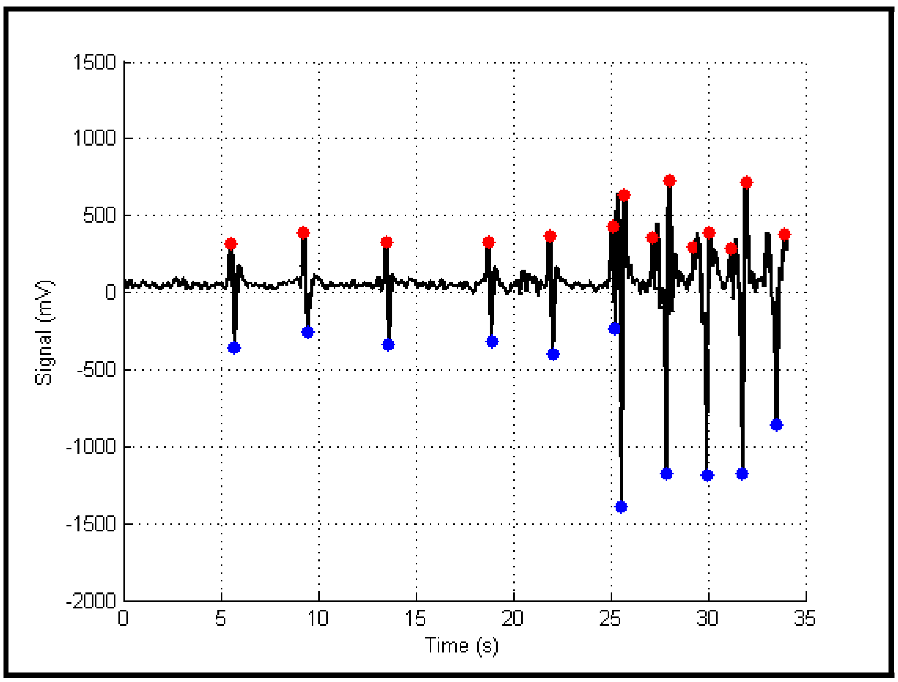

Fig. 12. Graphical representation of Test 1 showing the extracted EOG signal and blink detection. In this test, the participant made 6 involuntary blinks and 5 voluntary blinks. The system recorded 6 involuntary blinks and 5 voluntary blinks. Note that at 25 seconds, the participant made an involuntary blink and then immediately made a voluntary blink. In this trial, the participant was male #1.

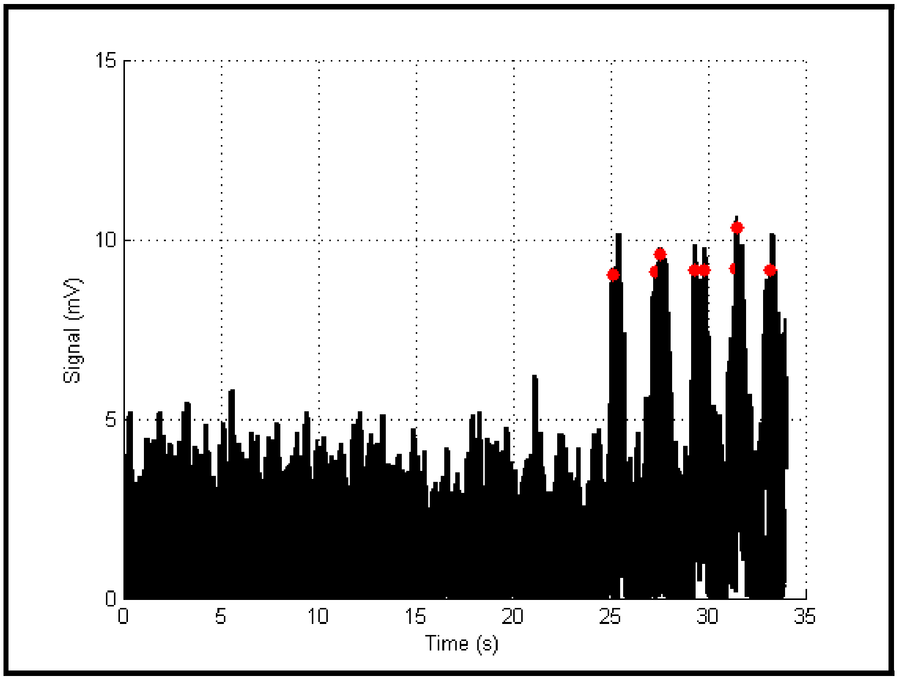

Fig. 13. Graphical representation of Test 1 showing the extracted EMG signal and blink detection. In this test, the participant made 6 involuntary blinks and 5 voluntary blinks. The system did not identify any involuntary blinks and 8 voluntary blinks. However, there are 5 distinct peaks, which correspond to the 5 voluntary blinks, which leads me to believe that the peak detecting algorithm needs adjustment. In this trial, the participant was male #1.

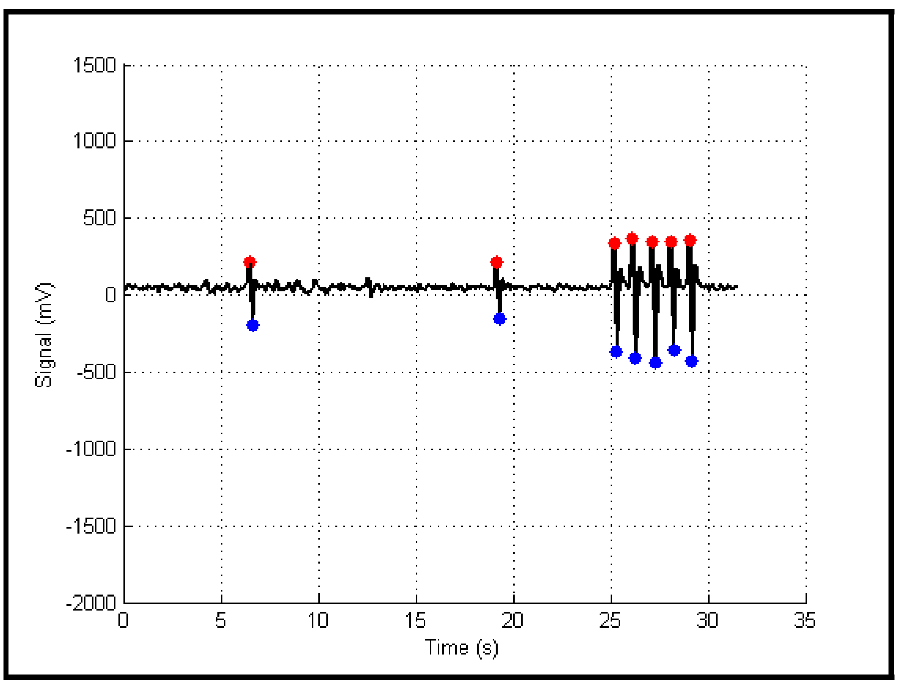

Fig. 14. Graphical representation of Test 1 showing the extracted EOG signal and blink detection. In this test, the participant made 2 involuntary blinks and 5 voluntary blinks. The system recorded 2 involuntary blinks and 5 voluntary blinks.In this trial, participant was male #2.

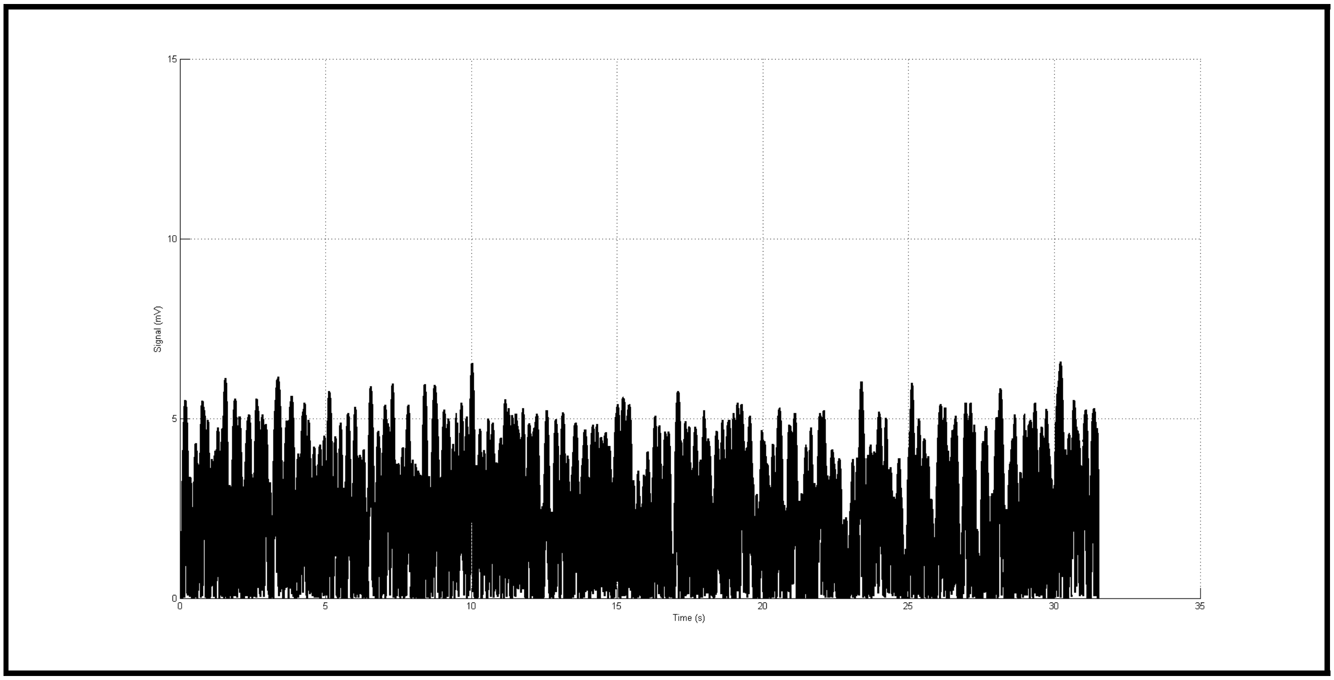

Fig. 15. Graphical representation of Test 1 showing the extracted EMG signal and blink detection. In this test, the participant made 2 involuntary blinks and 5 voluntary blinks. The system did not identify any involuntary blinks nor blinks. This leads us to believe that male #2 does not engage his facial muscles significantly while making intentional blinks.

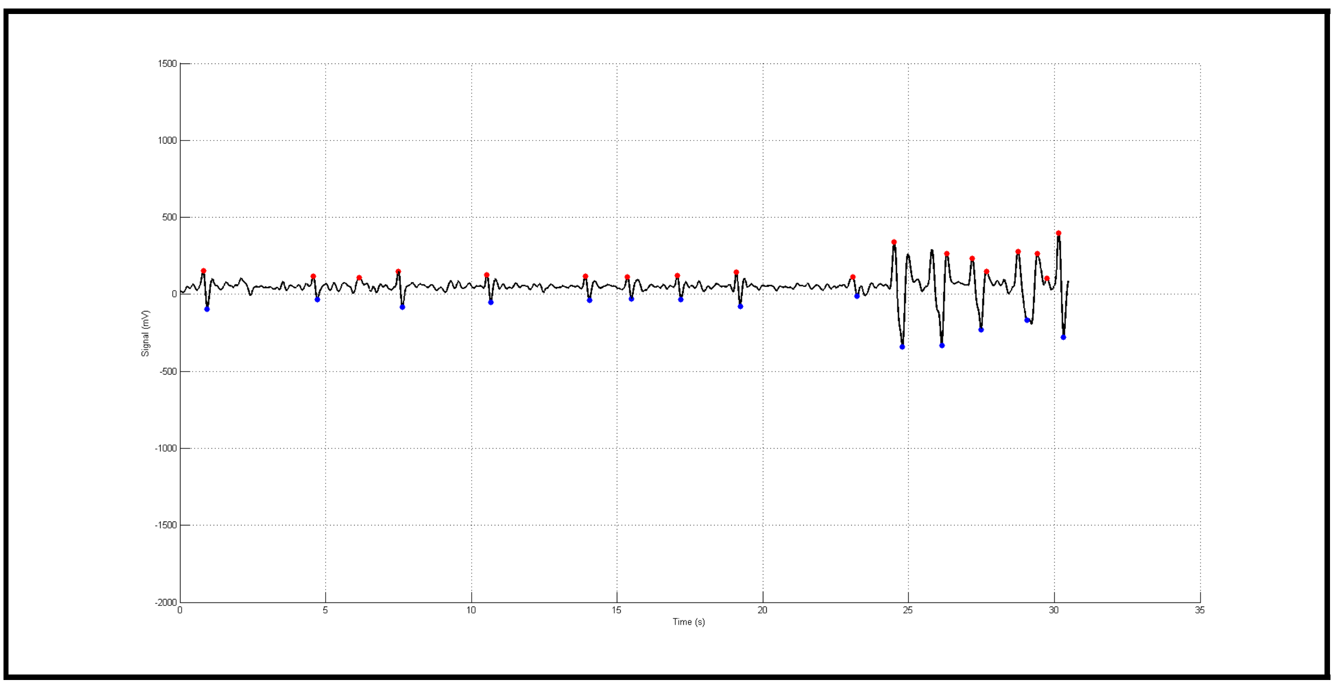

Fig. 16. Graphical representation of Test 1 showing the extracted EOG signal and blink detection. In this test, the participant made 9 involuntary blinks and 5 voluntary blinks. The system recorded 9 involuntary blinks and 5 voluntary blinks.In this trial, participant was female.

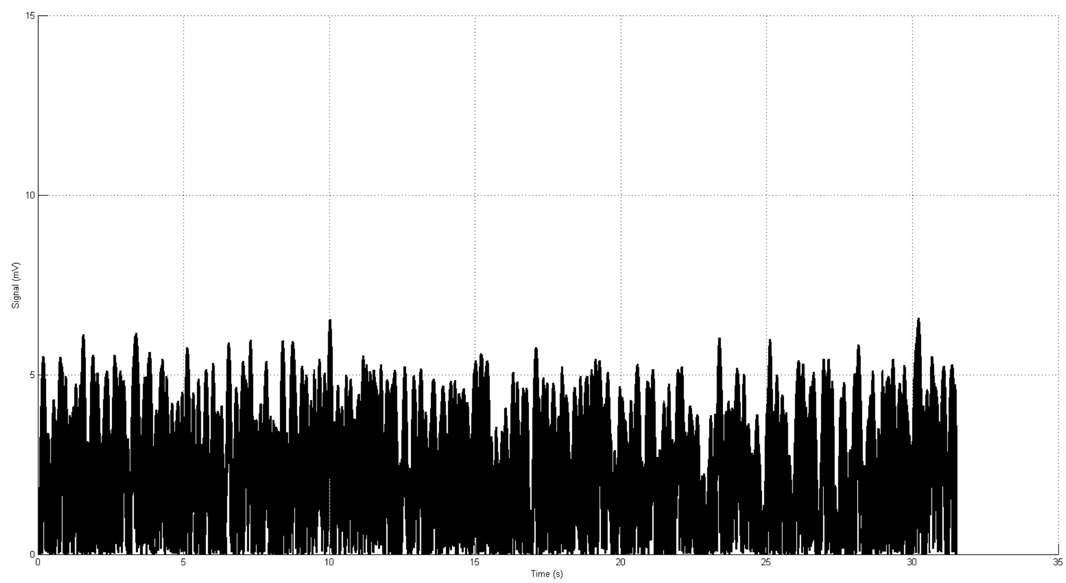

Fig. 17. Graphical representation of Test 1 showing the extracted EMG signal and blink detection. In this test, the participant made 9 involuntary blinks and 5 voluntary blinks. The system did not identify any involuntary blinks nor blinks. This leads us to believe that female participant does not engage her facial muscles significantly while making intentional blinks.

2) Test 2: Voluntary versus Involuntary Eye Movement:

The second type of experiment, called Test 2, was an experiment geared to provide data in determining voluntary versus involuntary eye movements. The participants were asked to look forward towards a computer screen for 15 seconds. Participants were asked to refrain from blinking. After the 15 second period, participants were asked to look up for a sustained 5 seconds, look down for a sustained 5 seconds, look left for a sustained 5 seconds, and look right for a sustained 5 seconds.

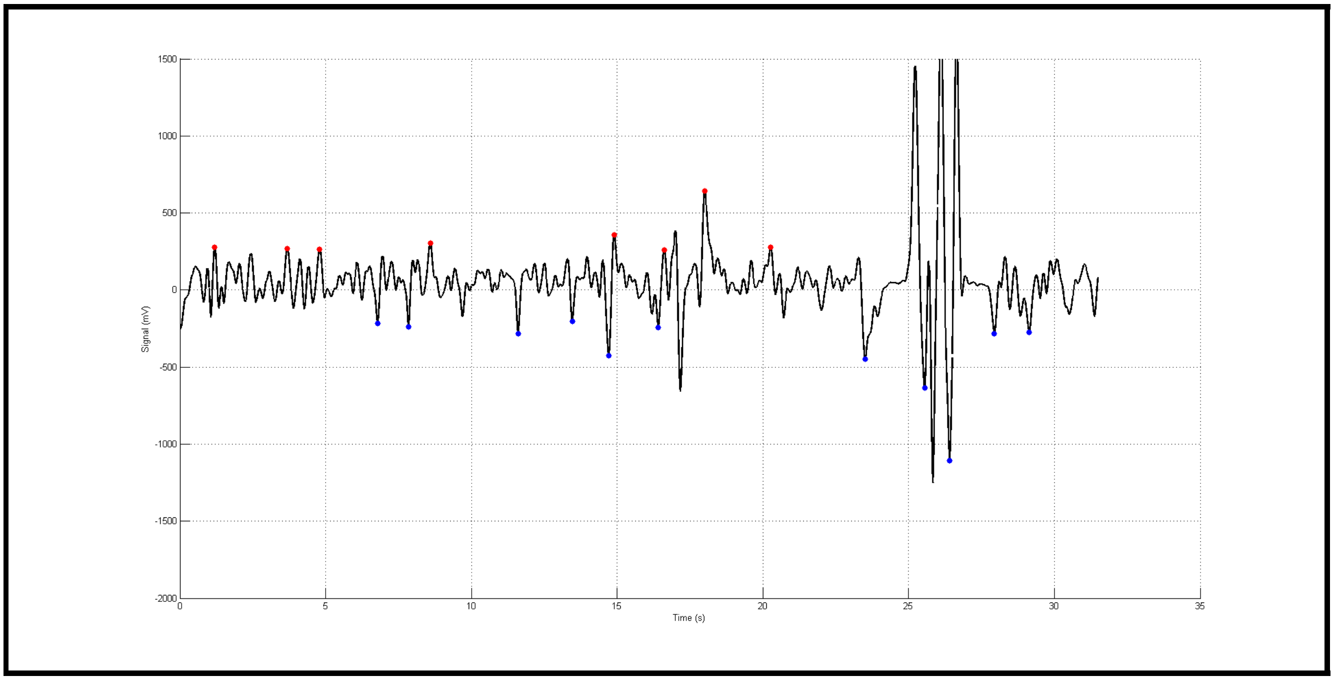

Fig. 18. Graphical representation of Test 2 showing the extracted EOG signal and eye direction movement. In this test, there is not an immediately discernable pattern to directional movement. More resarch will need to be done. (See ”Future Work”)

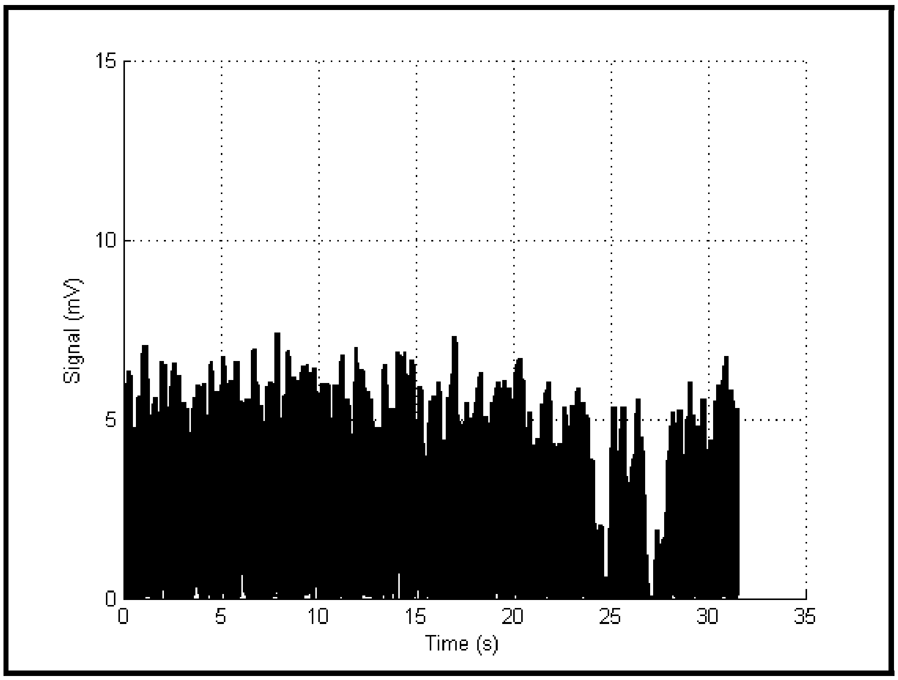

Fig. 19. Graphical representation of Test 2 showing the extracted EMG signal and eye direction movement. In this test, there is not an immediately discernable pattern to directional movement, with the exception of voluntary eye movement in the left direction. More resarch will need to be done. (See ”Future Work”)

B. Goal Evaluation

C. Voluntary Blink Detection Accuracy

In our experiments, we were able to detect an intentional blink 100% of the time. However, the wave-form for the female participant was significantly different than that of the male participant such that the tolerances of the system required recalibration between the two genders.

D. Involuntary Blink Detection Accuracy

In our experiments, we were able to detect an unintentional blink 100% of the time. However, the wave-form for the female participant's unintentional blinks were closer in amplitude and width such that the threshold between intentional and unintentional was much closer than that of the male participants.

E. Voluntary Eye-movement Detection Accuracy

A secondary goal is to accurately determine voluntary eye movements for the purpose of switching selections or moving a cursor. Unfortunately, we were unable to make any visual or computational distinctions between the four directions. However, we were able to distinguish, at least visually, the difference between looking forward and voluntarily looking in another direction. We were able to detect that an eye movement was made, but not the direction. Thus, for this criteria, we postpone evaluation until further research is conducted using blind-source separation methods such as ICA.

F. Involuntary Eye-movement Detection Accuracy

A complementary goal is to accurately determine involuntary eye movements for the purpose of reducing false-positive movements. Unfortunately, we were unable to make any visual or computational distinctions between the four directions and looking forward. We were able to detect that an eye movement was made, but not the direction. Thus, for this criteria, we postpone evaluation until further research is conducted using blind-source separation methods such as ICA.

TABLE II
THE FOLLOWING TABLE SHOWS A LIST OF CRITERIA TO WHICH THE SYSTEM HAS BEEN EVALUATED FOR SUCCESS.

Criteria	**Target**	**Result**	**Target Met**
Accuracy of voluntary blink detection	$\geq$ 80%	100%	Yes
Accuracy of involuntary blink detection	$\geq$ 80%	100%	Yes
Accuracy of voluntary eye-movement detection	$\geq$ 80%	50%	N/A*
Accuracy of involuntary eye-movement blink detection	$\geq$ 80%	0%	N/A*

Unfortunately, we were not able to discern directionality of eye movement with the MindWave Mobile. We were, however, able to discern, at least visually in the EOG signal, that the participant made an eye movement in the up and left directions. Since the MindWave's electrode is in a fixed position above the left eye, this implies that we are detecting the EOG contraction of the top and left muscles of the eye. Further investigation is required. ICA may be able to provide the other two directions. Thus, we cannot evaluate the last two criteria.

G. Future Work

We would like to further the work developed using an array of sensors to detect eye x,y position relative to the head or pursue ICA methods to develop an accurate sense of directionality. For applications with heads-up displays, such as Google Glass, a solution that employs EEG rather than a visual eye tracker may prove to create a more integrated solution.

VII. Conclusion

In conclusion, in this semester-long 91r project, we met our primary deliverable of producing a real-time EEG-based blink detection system that can discern between intentional and unintentional blinks. The system that was developed is relatively agnostic between different participants. The differences between participants was typically mitigated by adjusting the threshold and selectivity of the peak finder. For the three participants, the blink characteristics could easily be separated into two classes, voluntary and involuntary. Lastly, for only one participant, was the EMG a consistent mark for voluntary blinks. It seems possible that only some people strongly engage their facial muscles while blinking.

With regards to developing a model for directional eye movements with EEG, more research is required to develop ICA models that may possibly reveal hidden directionality markers. Principally, we are able to discern voluntary movement in the up and left direction of the eye, but we do not have an accurate way to discern movement in the other two directions. It is possible that ICA may be able to separate out a distinct waveform that are specific to the other two cardinal directions.

VIII. Acknowledgements

We would like to thank Professor Krzysztof Gajos for his advice and guidance. We also would like to thank the Harvard School of Engineering and Applied Sciences Undergraduate Teaching Labs for provisioning the Olimex OpenEEG device.

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