NeuroGaze in Virtual Reality: Assessing an EEG and Eye Tracking Interface Against Traditional Virtual Reality Input Devices

by

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ABSTRACT

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Abstract Requirements

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Dedicated to all my family, friends and colleagues who never stopped believing in me.

ACKNOWLEDGMENTS

Thank you to my thesis advisor committee – Dr. Joseph LaViola, Dr. Ryan McMahan, and Dr. Mohsen Rakhshan. Thank you to my research assistant, Kyle Coutray, for assistance with the design and implementation of the NeuroGaze system. Additionally, thanks to all the members of UCF’S Interactive Systems and User Experience (ISUE) Lab whose unconditional support was vital to the completion of this work.

Finally, thank you to my loving family and friends for always pushing me to achieve more than I ever could alone.

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# LIST OF ABBREVIATIONS

HCI

BCI

VR

AR

MR

3DUI

EEG

FNIRS

VE

POC

Remember to alphabetize the entries in this section.

# CHAPTER ONE: INTRODUCTION

## 1.1 Motivation

For as long as I can remember, I have been obsessed with the idea of living in a virtual world. A world like the one we currently live in but enhanced in a way that only a truly digital world could. As a mixed reality engineer (MRE), building experience in virtual reality (VR) is the closest I’ve come to living in this “New World.” However, no matter how immersive or present I feel within these virtual worlds, the methods in which I interact with these worlds have always made me feel disconnected from the environment. We don’t interact with our current environment by clicking buttons to grab a cup so why should interacting with a virtual environment (VE) be any different?

The discovery of brain computer interfaces (BCI) led me to wonder what applications the technology might have in VEs. Selection within VEs is where I felt the most disconnected with the environment due to traditional 3D user interfaces (3DUI) such as VR controllers. Prior research has been done to show that electroencephalogram (EEG) recordings from the brain and eye gaze can be used to interact with computers []. Other research utilizing VR investigate how EEG and eye gaze can be used to evaluate engagement **[https://onlinelibrary.wiley.com/doi/full/10.1111/jcal.12595?casa\_token=-MefuWLIK-QAAAAA%3AiM09ff7TuYogM\_JtQ07hGP0I1Zau6tiIc9Kb4BxAJqLcUXHjDC8P6r1naRE9uC\_secQrFeHtKbkCb1su]** or how eye movement artifacts found within EEG readings during VR simulations can be used to build artifact correction methods **[https://www.frontiersin.org/articles/10.3389/fnhum.2012.00278/full]** Research involving BCI in VR use VR as a medium to simulate environments not easily replicable in the non-VEs in order to record EEG data but do not attempt to segment and classify artifacts in EEG streams with the purpose of selection in VR. While the current

## 1.2 VR & 3D User Interface Interaction Techniques

Excerpt on VR 3DUI techniques, poll showing most popular? Reference Joe’s 3DUI book here.

Include short section on VR and HMD?

### 1.2.1 NeuroGaze – Eye Tracking & Electroencephalogram

NeuroGaze is a novel 3DUI interaction technique we developed that utilizes infrared (IR) cameras built into a VR head mounted display (HMD) to track where a user is looking in a VE. NeuroGaze also uses EEG to determine when a user would like to select an object once they have both looked at the object and thought about selecting it. This technique aims to provide users with a more intuitive experience when selecting objects in VR while continuing to maintain the level of reliability users would expect when using traditional interaction methods (e.g. VR controllers).

**IMAGE OF NEUROGAZE**

### 1.2.2 Eye Gaze & Hand Tracking

Eye gaze and hand tracking is a selection method that uses eye tracking for users to “hover” over objects they would like to select and hand tracking to select or interact with objects. The “trigger” for these hand tracking actions is usually done utilizing gestures. Gestures use specific hand movement and positions to specify a command in a VE [https://www.researchgate.net/publication/317173375\_Design\_of\_Hand\_Gestures\_for\_Manipulating\_Objects\_in\_Virtual\_Reality]. Specific to our evaluation, participants used a pinch gesture to select objects within the VE. This technique is used by the Apple Vision Pro for all selection within the AR environment.

**IMAGE OF EYE TRACKING with pinch gesture**

### 1.2.3 VR Controllers

VR controllers are handheld devices that allow users to interact with VE in an intuitive way. They are designed to be used as selection devices enabling users to navigate through menus, select items and interact with objects within a VE. For selection, participants will use a point and click interaction technique where a ray will be cast from the end of the VR controllers that participants can use to determine where they can interact with the VE and the controller triggers are used to selection objects. VR controllers allow users to have precise control over selection and manipulation tasks but can be physically tiring when used for a longer duration [https://www.mdpi.com/2227-9709/8/3/60#B14-informatics-08-00060].

**IMAGE OF VR CONTROLLERS**

# CHAPTER TWO: LITERATURE REVIEW

## 2.1 Input Modalities in Virtual Reality

## 2.1.1 VR Controllers

Early VR systems relied on basic input devices such as keyboards, mice or joysticks, which did not provide a natural or intuitive way to interact with VEs. The development of dedicated VR controllers marked a significant advancement, offering users a more immersive and hands-on VR experience. Point-and-click, like a mouse and keyboard in traditional computer interfaces, is a widely used interaction technique in VR. Studies have investigated the efficiency and accuracy of point-and-click interactions using VR controllers, highlighting their effectiveness for selection and manipulating objects in 3D space. Over the years, research has been done expanding on these devices in new in interesting ways with the goal of building upon the initial VR controllers.

An example of this can be seen in Whitmire et al [High-Fidelity Interaction for Virtual and Augmented Reality] who developed a unique handheld controller, denoted the *Haptic Revolver*, utilizing an actuated wheel. As participants spin a haptic wheel on the controller to move around the VE, the controller provides users with tactical feedback that can be interchanged with different wheels. This allows users to experience a variety of accurate haptic information depending on the VR scene. Although haptics is outside of the scope of this Thesis and the NeuroGaze system does not include haptic feedback, it is important to recognize the use of haptics to provide users with a more intuitive and immersive experience.

Fahmi et al. [<https://iopscience.iop.org/article/10.1088/1757-899X/851/1/012024/meta>] investigated the overall user experience of VIVE VR controllers when compared to a Leap Motion Controller (LMC) and Senso Gloves. LMCs uses a infrared monochromic camera that periodically takes pictures [<https://iopscience.iop.org/article/10.1088/1757-899X/851/1/012024/meta> , Rahmat R F, Hasibuan RH, Siregar B, Syahputra MF 2018 A traditional bekel game using leap motion controller Journal of Physics: Conference Series, 1116(2), 022036.]. An observation area is set and when a user's hand enters this area, the hand gestures are recorded, and an action is performed in VR [Nowicki MR, Pilarczyk O, Wasikowski J and Zjawin K 2014 Gesture Recognition Library For Leap Motion Controller]. Senso Gloves are wireless devices that uses Inertia Measurement Unit (IMU) sensors to observe hand and finger movement This device also includes haptic feed in the form of vibrators in the fingertips, back of hand and wrists [Perret J and Vander PE 2018 Touching Virtual Reality: a Review of Haptic Gloves Proceedings of 16th International Conference on New Actuators, pp. 270–274.]. When a user experience study was conducted, high Likert scale values for the VIVE VR controllers suggested that participants felt that VR controllers were very interactive, and the controls were easy to learn and use. When ideating on how to use EEG effectively as a part of the NeuroGaze input device, the first challenge was how to leverage a user's previous experience with input devices such as VR controllers. Although NeuroGaze does not use VR controllers, the system should still feel intuitive and easy to use. Studies like Fahmi et all showed me that if I was able to make NeuroGaze as highly interactive, intuitive and satisfying to use as VR controllers then participants would report a positive user experience. User experience when compared to VR controllers is only half of the battle, the input system should also perform tasks successfully and effectively. Luong et al. [Controllers or Bare Hands? A Controlled Evaluation of Input Techniques on Interaction Performance and Exertion in Virtual Reality] evaluates the interaction performance of VR controllers when compared to hand controllers. Both input devices utilize the virtual pointer metaphor which alleviates a major shortcoming of both input devices: interacting with objects that are out of reach [F. Argelaguet and C. Andujar. A survey of 3d object selection techniques for virtual environments. Computers & Graphics, 37(3):121–136, 2013, D. Mendes, F. M. Caputo, A. Giachetti, A. Ferreira, and J. Jorge. A survey on 3d virtual object manipulation: From the desktop to immersive virtual environments. In Computer graphics forum, vol. 38, pp. 21–45. Wiley Online Library, 2019.]. This study showed that for the interactions, participants preferred VR controllers with ray cast because of the precision they could get. Additionally, these participants performed better when evaluated on both speed and accuracy than they did while using the virtual hand. It was decided that NeuroGaze would use some type of ray casting as the interaction metaphor of choice due to its speed and intuitiveness to use. However, a common complaint with using the ray pointing with VR controllers for longer durations is physical strain. In research evaluating this input device and metaphor, participants start to hold the controller closer to their body to reduce fatigue [F. Argelaguet and C. Andujar. A survey of 3d object selection techniques for virtual environments. Computers & Graphics, 37(3):121–136, 2013, D. Mendes, F. M. Caputo, A. Giachetti, A. Ferreira, and J. Jorge. A survey on 3d virtual object manipulation: From the desktop to immersive virtual environments. In Computer graphics forum, vol. 38, pp. 21–45. Wiley Online Library, 2019.]. For this reason, it was determined that the NeuroGaze system would not be using VR controllers despite its intuitiveness to use. Looking deeper into how prolonged use of input devices can cause fatigue, I investigated input devices that were compatible with the ray casting metaphor [A survey of 3D object selection techniques for virtual environments Author links open overlay panel Ferran Argelaguet] but did not induce as much physical effort as VR controllers over longer durations of time. The next steps in developing the NeuroGaze system pointed towards eye tracking as a possible input device for VEs.

## 2.1.2 Eye Gaze

INCLUDE FIGURES FOR EYE GAZE AS WHOLE OR FOR HOW THEY WORK

INCLUDE IMAGE FOR ALL 4 EYE TRACKING

Eye gaze uses eye tracking technology to measure a user's gaze direction, or where the person is looking, and the movement of the users' eyes. This input method is usually achieved with infrared cameras that illuminate the eye by refracting light off the cornea and the retina to create distinct patterns, called glints. Software like RemoteEye developed by Hosp et al. [RemoteEye: An open-source high-speed remote eye tracker] uses glint detection algorithms to calculate the gaze point and achieve high speed eye tracking capabilities. When applied to VR as an input device in VEs, an entire genre of interaction technique presents itself. Novel techniques like the ones evaluated by Piumsomboon et al. [Exploring Natural Eye-Gaze-Based Interaction for Immersive Virtual Reality], show us the versatility of the eye gaze input device. In this evaluation, three selection techniques based on eye gaze were evaluated. The first, *Duo-Reticles*, uses one eye-gaze and one inertial reticle to perform selection. *Radial Pursuit* specializes in selecting cluttered objects with smooth pursuit. *Nod and Roll* is a hand gesture-based interaction based on the vestibulo-ocular reflex. These techniques in combination highlighted the four primary natural types of eye movements [K. Rayner. Eye movements in reading and information processing: 20 years of research. Psychological bulletin, 124, (3), pp. 372, 1998] that should be studied when constructing an eye gaze-based technique for selection. These include (1) *saccade*, a quick eye movement with a fixed end target, demonstrated by Duo-Reticles, (2) *smooth pursuit*, a smooth eye movement towards a moving target, demonstrated by Radial Pursuit, (3) vestibulo-ocular reflex (VOR), an automatic eye movement that counters head movement when a user's gaze is fixed on a target, demonstrated by Nod and Roll and finally (4) vergence, when our eyes converge or diverge to look at targets of varying distance. Participants were tasked with finding a matching picture as quickly and accurately as possible. Participants were then asked to answer a 7-point Likert scale usability questionnaire that asked participants to rank the input devices with statements like “It felt natural the use” and “I felt satisfied using it.” The results showed that the Duo-Reticle was highly favored even if the results did not yield a high difference compared to the other input devices. When considering eye gaze and a part of the NeuroGaze input device, we needed to decide not only what technique to use with this input device but also which would be best for our experimental design. At an early stage in our experimental design, we wanted to focus on moving targets but as we learned more about EEG, we realized that limiting kinematic activity, especially head movement, would be greatly beneficial to the success of a BCI. The evaluation of input methods that take advantage of saccade [https://www.frontiersin.org/journals/psychiatry/articles/10.3389/fpsyt.2020.572938/full], such as Duo-Reticles, showed us how NeuroGaze could take advantage of the eyes natural ability to rapidly update to new stationary targets. With this in mind, we were curious how quickly the eye could update to a new stationary target when compared to existing fast input methods like VR controllers.

Francisco et al. [A Comparative Study of Eye Tracking and Hand Controller for Aiming Tasks in Virtual Reality] evaluated VR controller accuracy when compared to an eye gaze technique using previously mentioned ray casting metaphor to perform aiming selection tasks [A survey of 3D object selection techniques for virtual environments Author links open overlay panel Ferran Argelaguet]. To evaluate how demanding the input devices were, a raw NASA-TLX survey was distributed to participants. A system usability scale (SUS) survey was used to Participants were asked to complete an eye tracking calibration test before using their eye gaze to look at a target of interest and use VR controllers to select the object. The same evaluation was performed with VR controllers with a point and click technique. The evaluation results showed that the eye gaze input method performed on par with VR controllers. The survey results showed participants felt that the eye gaze input method produced a lower Physical Demand and Effort than VR controllers. At this point in our literature review we were able to determine that eye tracking is not only as performant and VR controllers, but also produces less physical demand and effort than VR controllers when selecting fixed target. Under varying fields of view (FOV), eye gaze even performed over head-gaze based selection [Advantages of Eye-Gaze over Head-Gaze-Based Selection in Virtual and Augmented Reality under Varying Field of Views Jonas Blattgerste, K. Rayner. Eye movements in reading and information processing: 20 years of research.]. Based on our research, eye tracking seemed to be the most precise and intuitive way to allow users in a VE to show intent for selecting an item. With BCIs still in our minds, we turned towards research in this area and the best techniques, hardware and strategies for integration with eye gaze given the limitations and scope of this Thesis.

## 2.1.3 Brain Computer Interfaces

Brain computer interfaces harness neural signals that are usually translated into commands that can control some computer system. The area of study has broadened itself in the last 15 years and its applications have increased in range including technologies like robotics, Internet of Things (IoT) , and VR [Brain–computer interfaces for communication and control Jonathan R. Wolpawa,b,\*]. In recent years, invasive neural interfaces have seen human testing, such as intracortical recordings. This process involves implanting neural interfaces composed of biocompatible materials with the goal of curing existing limitations of a participant or enhancing them [Grillner, S., Ip, N., Koch, C., Koroshetz, W., Okano, H., Polachek, M., et al. (2016). Worldwide initiatives to advance brain research. Nat. Neurosci. 19, 1118–1122. doi: 10.1038/nn.4371]. While it is important to be cognizant of invasive interfaces, this scope of this Thesis is strictly focused on signal acquisition using non-invasive methods (e.g. EEG).

Electroencephalogram or EEG is a non-invasive recording of electrical activity along the scalp. Specifically, EEG is the measure of the voltage fluctuations resulting from ionic current flows within the neurons in the brain. [Analysis of EEG Using 10:20 Electrode System Manzoor Khazi]. EEG data has been used in a variety of uses cases such as medical diagnostics for neurological disorders [2007 AASM scoring manual], cognitive and behavior and behavior research and BCIs. With a multitude of areas of research using EEGs, standards must be practiced when placing electrodes on the scalp or it becomes difficult to compare EEG data across evaluations. The collection of EEG data is dependent on the electrode system chosen.

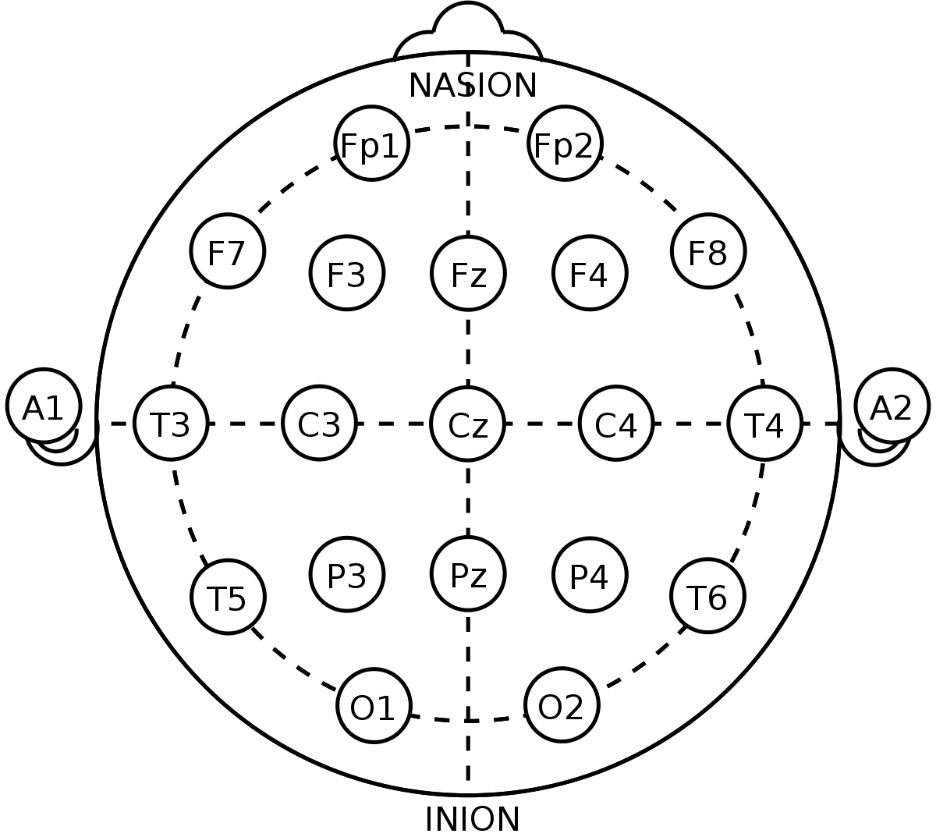


Figure 1: Electrode locations of International 10-20 system for EEG recording

The 10-20 electrode system, or International 10-20 system, is an internally recognized method to describe and apply the location on scalp electrodes in the context of an EEG test or experiment [Analysis of EEG Using 10:20 Electrode System Manzoor Khazi]. In Figure #, we can observe a top-down view of the head where the Nasion, the depressed area between the eyes, is the front of the head, and the Inion, the crest of the back of the skull, is the back of the head. The “10” and “20” refers to the 10% or 20% of spacing between each adjacent electrode, starting from ear to ear. The starting letter is used to identify a lobe or area of the brain: central (C), occipital (O), parietal (P), temporal (T), and pre-frontal (Fp). The following number represents the side of the brain where even numbers (2,4,6,8) represent the electrodes on the right side of the brain and odd numbers (1,3,5,7) represent the left side of the brain. With standardized electrode placement, researchers build upon previous works with little variances in electrode placement on a participant's scalp. It should be noted that other systems exist such as 10/5, 10/10 exist are not internationally recognized nor do they have noticeable performance increase when evaluating quality of the EEG data [https://www.sciencedirect.com/science/article/abs/pii/S1053811906009724?casa\_token=hEO6WI5Emm4AAAAA:hRlDgPEmbejWtR8pykKbX5WU6ChbZJ8bsopzlR51SYnM3nEpPyG5fu8FHSg1cRZKfWdNFWmknjA]. The 10-20 system is the current standard when collecting EEG data and NeuroGaze is compliant with this standard. Until other electrode placement standards are established or new positioning systems [https://pubmed.ncbi.nlm.nih.gov/26082845/] are created and tested through roughly, we do not plan to diverge from this standard.

Larsen et al. [A method for synchronized use of EEG and eye tracking in fully immersive VR] recently published a paper evaluating selection in VR using a similar input method as NeuroGaze. The paper showcased a proof of concept (POC) called *SSVEP-Speller* which uses eye trackers to make a preselection of a subsection of a virtual 3D keyboard to select a letter. EEG is used to measure the temporal difference between the time it takes to completely close the eyes during a blink. Electrodes were placed over the occipital region at O1, Oz, O2, P3, P7, Pz, P8 and P4 to record EEG data of the visual stimuli. To collect data for their temporal blink classifier, participants were instructed to wear the EEG headset while holding a VR headset to their head and blink naturally with both eyes at about a rate of 60 beats per minute (BPM). During evaluation, participants were tasked with looking at letters they wanted to select while varying levels of flickering occurred, turning their screen completely black, to simulate a blinking sensation. The results showed that these researchers were successfully able classify intervals of blinking to minimize jittering that occurs during blinking during selection with eye gaze. This paper educated us on the effects of noise in an EEG data stream because of blinking. While NeuroGaze does not utilize a pretrained machine learning model for classifying noise caused by blinking, this paper solidified our decision to find a software that would handle this filtering for us. In initial pilots of the NeuroGaze system we did experience issues with jittering due to blinking due to this being handled for us in the Meta Quest Pro HMD. Future work, independent of the Meta Quest Pro HMD, could benefit from software like Blink [Blink: A Fully Automated Unsupervised Algorithm for Eye-Blink Detection in EEG Signals], designed to manage noise potentially inferring with eye tracking data.

Putze et al. [https://dl.acm.org/doi/10.1145/2993148.2993199] presents research closest to our latest version of the NeuroGaze input device. Interestingly, their selection device was designed for use not in immersive or 3D environments typical of VR, but rather in 2D or screen-based environments. This distinction is crucial, as it emphasizes the different challenges and interaction dynamics present in non-immersive verses immersive settings. Their system, denoted *EEG+GAZE*, consists of Tobii X60 eye tracker with a sampler frequency of 60Hz and a BrainProducts 32 electrode EEG cap. Participants had 29 electrodes positioned respective of the 10-20 system at the following locations: Fp1, Fz, F3, F7, FT9, FC5, FC1, C3, T7, CP5, CP1, P3, Pz, P7, O1, Oz, O2, P4, CP6, CP2, Cz, C4, T8, FT10, FC6, FC2, F4, F8, FP2 and reference electrode positioned at Fz. EEG+GAZE used gaze to detect when a user is likely and unlikely to select an object. This is achieved by monitoring when a user is slowly moving their eyes towards an area of interest versus quickly scanning the screen. During the window where a user's gaze seems like they want to interact with an object, the EEG headset records their temporal window. Data to train the classifier for the eye gaze and EEG, participants were tasked with following key on a monitor with their eyes and in the moments where the objects speed increased and slowed down, the data coming from these two devices created a window of interest. The evaluation consisted of 10-fold cross validation for each participant individually and averaged the result. The data shows that their classifier produced a lower the lower the tolerance measured in number of window and milliseconds. This suggests that their EYE+GAZE systems classifier had very limited false positive and thus more accurate classification for event-based evaluation scenes [Combining Eye Gaze Input With a Brain–Computer Interface for Touchless Human–Computer Interaction].

This literature review has shown the process of deciding the design of the NeuroGaze system by breaking apart this new input device's subcomponents. VR controllers presenting us with the ray casting interaction metaphor, eye gaze provided us with comparable saccade interaction methods, like Duo-Reticles, and evaluation with fixed points in a 3D environment for our evaluation of the system. Finally, an overview of the research done in BCI in 2D, and 3D environments shows us that it is possible to classify these variances in neuron voltage. Putting this all together, we get the NeuroGaze input device that aims to challenge how quickly, accurately and intuitively a 3DUI input device can be in VR.

# CHAPTER THREE: SOFTWARE & SYSTEM DESIGN – NEUROGAZE

## 3.1 System Overview

NeuroGaze is an input device proof of concept (POC) specifically developed for selection in a VE. The objective of NeuroGaze is to empower users with a selection device that allows them to interact in VR in a new way to improve accuracy and efficiency when compared to traditional input devices such as VR controllers. Our system uses eye trackers built into the Meta Quest Pro HMD to activate a “hover state” on objects in the scene they can interact with. When a user's eye gaze is broken by one of these interactable objects, the object slowly and continuously grows until it reaches its max size. Similarly, when a user's eye gaze moves off an interactable object, the object will shrink at a slow continuous speed until it is returned to its original scale. The users eye gaze interacts with objects in the scene using the ray cast interaction metaphor and a white line renderer to represent the midpoint between each of the users' eyes at any moment. NeuroGaze uses the Emotiv Epoc X EEG headset for the EEG data stream and the EmotivBCI program for creating training profiles that collect EEG data and handle EEG noise sanitization and EEG artifact classification. The Unity Game engine and Meta All in One SDK were used to complete the development of NeuroGaze, integrating the hardware components and software solutions to create a seamless and intuitive user experience within VE. This integration allows NeuroGaze to provide a hands-free, efficient, and precise method for interacting with and selecting objects in VR, showcasing a significant improvement over conventional input devices in terms of user engagement and interaction fidelity. The implementation of NeuroGaze represents a novel approach to VR interaction, leveraging the precision of eye tracking and the sophistication of EEG data analysis to facilitate a more natural and immersive experience. By utilizing the Emotiv Epoc X EEG headset and EmotivBCI software, NeuroGaze effectively minimizes noise and accurately classifies user intentions based on neural activity, demonstrating the potential of combining multiple biometric inputs for enhanced control within a VE.

Throughout the development process, a user-centered design philosophy [3D User Interfaces: Theory and Practice (Usability) 2nd Edition] was emphasized, ensuring that NeuroGaze not only advances the technological capabilities of VR interfaces but also addresses the practical needs and preferences of users. By focusing on ease of use, accessibility, and the reduction of physical exertion, NeuroGaze aims to make virtual interactions more enjoyable and less tiring, particularly for users who may find traditional input devices cumbersome or completely inaccessible.

## 3.2 EEG Hardware

When deciding which EEG headset to use for the NeuroGaze system, our immediate concern was ensuring we chose a headset that gave us a high-fidelity EEG stream that was budget efficient. We wanted to keep our budget in the $1000 range or less due to this Thesis not being funded. Additionally, from an ergonomics perspective, we needed to ensure that the EEG headset could be worn underneath the Meta Quest Pro VR HMD. If possible, we also would prefer the electrodes to be in a different position than the position where the VR headset would be holding the user. Although we are limited by these two pieces of hardware not designed for one another, if we can reduce pressure points on the user's head, this would greatly increase comfort and reduce unnecessary artifacts from discomfort. Getting data off these headsets was also a factor we had to consider. How many channels do we need to access? How does the EEG data export and does the headset interface with any existing data collection, synthesis and machine learning software? All these unknowns needed to be investigated and the most “out of the box” functionality we could get for our hardware POC was ideal. We reviewed many different EEG headsets, but the following were the three we narrowed down for the final design for the NeuroGaze input device.

### 3.2.1 Emotiv Insight II

Emotiv is a pioneer in the field of neuroscience with its development of high-quality, accessible EEG technology. Their products are used across the world for research, neuroeducation, and brain computer applications, focusing on producing comprehensive brain monitoring solutions. Emotiv’s commercial EEG headset was not only budget friendly but also would aid with tracking the quality of the EEG data we were collecting through the EmotivPRO and EmotivBCI programs. The Insight II model from Emotiv has 5 channels with 2 reference sensors, focusing on key areas of cognitive state monitoring. The polymer sensors are arranged according to the international 10-20 system and the location of the sensors are in the AF3, AF4, T7, T8 and Pz positions as seen in Figure #.

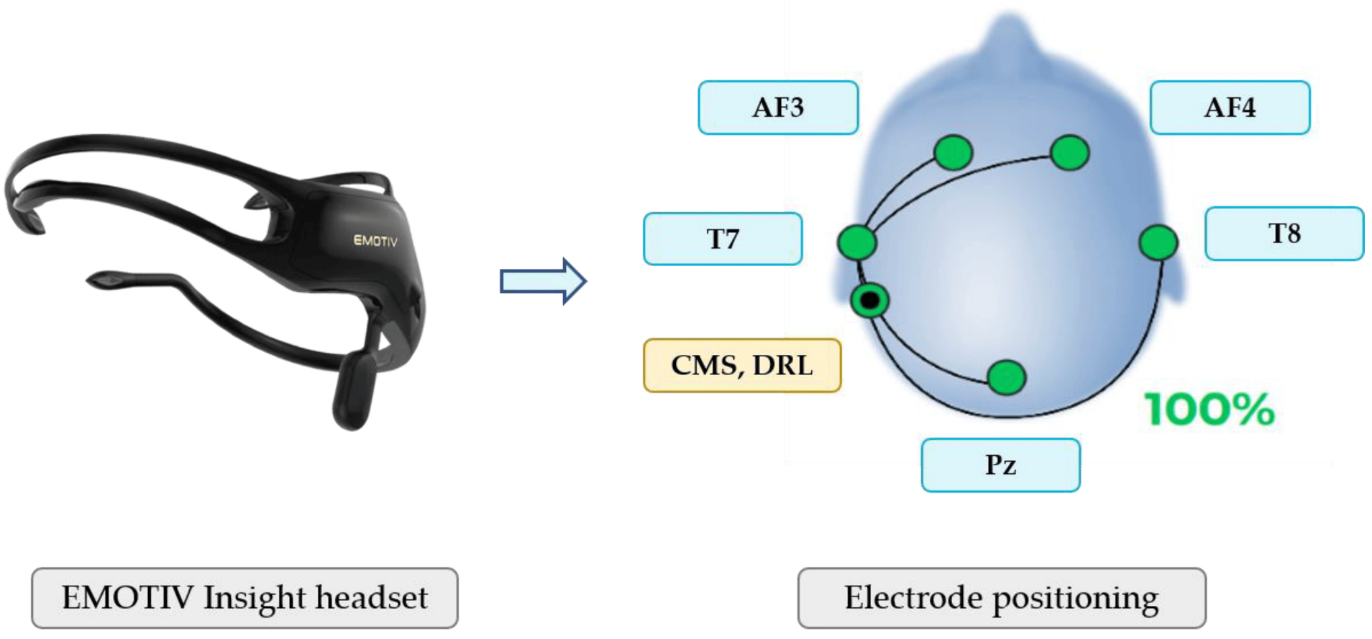


Figure 2: Emotiv Insight II (left) and electrode placement (right)

These sensor locations focus on the frontal and parietal areas which are important for cognitive and emotional insight. This headset has a sampling rate of up to 128HZ and connects to any computer that supports a Bluetooth 4.0 connection. We used this headset for a couple weeks, and while the contact quality was good, this headset was very uncomfortable to use for a longer period. This is partially because the Meta Quest Pro HMD distributes its weight to the front of the headset and the AF3 and AF3 electrodes are in this same position. Additionally, these two nodes were required to be a three-pronged contactor (See Figure #) which was very uncomfortable and sometimes even painful to wear for a prolonged period while wearing the Meta Quest Pro.

A black and green plastic object

Description automatically generated

Figure 3: Emotiv Insight II polymer sensors: three pronged (left), one pronged (right)

For this reason, we removed this headset from our apparatus and looked for alternatives for the NeuroGaze input device.

### 3.2.2 Muse II

Muse is another contributor to the neurotechnology space, offering devices that promote mental wellness through guided meditation and biofeedback. They offer the Muse II, a commercial EEG headband that is the more cost efficient of the three EEG devices we were interested in using. Additionally, this device is a hand band not a headset so the device did not have any nodes or prongs that could be uncomfortable to wear. The EEG headband consists of 5 EEG sensors along the forehand (3 reference sensors, 2 EEG sensors), one grounding sensor behind each ear and a heart monitor (See Figure #). The Muse II is worn like a pair of glasses making it perfect when paired with the Meta Quest Pro HMD and although there are sensors on the front of the headset in the forehead area, because these sensors are flat, they did not cause discomfort.

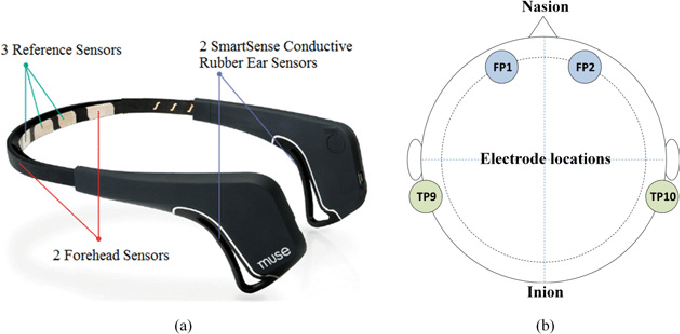


Figure 4: (a) Muse II EEG Headband with sensor locations, (b) electrode locations in International 10-20 system [A Pilot Study on Electroencephalogram-based Evaluation of Visually Induced Motion Sickness]

To pull the stream and visualize the EEG data from the headset and store it, we attempted to use the open-source application Mind Monitor (See Figure #). To classify data, we used Edge Impulse to import the raw data recorded from Mind Monitor and construct a neural network classifier. We collected data on thinking right, left and neutral in 5 second increments per thought. The data is stored as one CSV per session that Edge Impulse can use for an 80/20 training-testing split. Once the model trained on our data, the model performed inference with our testing split with a highest accuracy of 40%. After testing this pipeline further, we concluded that the noise artifacts impeded within the EEG data were clouding the data too much to classify intent with any level of confidence.

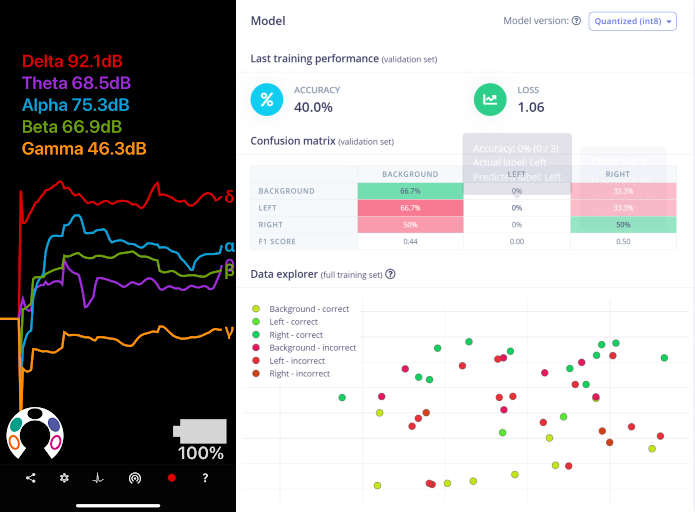


Figure 5: Mind Monitor visual of EEG data to be exported, (b) inference performed on Edge Impulse model trained on EEG data from Mind Monitor

The drawbacks of this headset are the limited channels we have access to for streaming EEG data, additionally the Muse SDK lacks any functionality for cleaning or classifying the data. If we selected this device, we would be required to collect ample data to train our own machine learning classifiers for identifying noise artifacts (e.g. eye blinks, random kinematic movements) and identifying when a user wants to interact with an object in the scene. Due to time restrictions and the POC nature of the NeuroGaze input device, we did not want to dedicate resources to machine learning classifiers and instead wanted to focus on finding the best configuration and techniques to use. For this reason, we chose not to use this headset and looked towards less cost efficient Emotiv headsets that can handle our data processing pipeline.

### 3.2.3 EMOTIV EPOC X

A magnifying glass and a diagram of a molecule

Description automatically generated

Figure 6: (a) Emotiv Epoc X EEG headset, (b) International 10-20 electrode placement for Emotiv Epoc X

When choosing the EEG headset for the NeuroGaze system, considering extended beyond technical specifications to consider factors such as user comfort, integration ease, and application relevance. The Emotiv Epox X stands out for its comprehensive 10-20 system channel coverage (sensors: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, references: TP9, P3, P4, TP10) and an extensive software ecosystem (See Figure #b). Although this headset is the most cost inefficient of the three candidates, we decided it was well worth it. Despite its functionality and integration possibility while being a commercial headset, the location of its electrode connections makes it ideal for compliance with the ergonomics of the Meta Quest Pro VR HMD. Additionally, the nodes are made of felt and saline solution can be added through the refillable sensor hole located on each sensor (See Figure #a). This design allows for maximum comfort, even at pressure points, and easy access to wetting dried out electrodes with saline solution even after the user has configured the NeuroGaze system. During evaluation participants are told to think of a motor command they would perform if they actually physically perform if they weren’t in a VE. With this in mind, we wanted to understand how effective the Emotiv Epoc X would be with classifying motor imagery and how internal motor act rehearsed in working memory [The neurophysiological basis of motor imagery Author links open overlay panel Jean Decety]. Fakhruzzaman et al. [EEG Wave Identification in Human Brain with Emotiv EPOC for Motor Imagery] used the Emotiv Epoc X to attempt to classify motor imagery using BCI scenarios. Participants were told to imagine the motor action they would prefer during the following testing scenarios:

1. Left Hand Movement
2. Right Foot Movement
3. Simultaneous Left Hand and Right-Hand Movement
4. Simultaneous Left-Hand Movement and Head Nodding
5. Simultaneous Right Foot and Left Foot Movement
6. Simultaneous Right Foot Movement and Head Nodding

When attempting to classify the EEG data that correlate to these motor imageries, the Scenario 1 test results had a 76.67% success rate, Scenario 2 test results showed a 91.67% success rate, Scenario 3 yielded a 28.33% success rate, Scenario 4 get 13.33% success rate, Scenario 5 showed 60% success rate and Scenario 6 success rate was 53.33% success rate. The main take aways from this study is that the Emotiv Epoc X could not handle complex motor imagery classification so we would need to limit participants to a single, consistent thought (e.g thinking of selecting objects with their dominant hand). Additionally, the paper commented that while the classification for these tasks is not amazing, for a consumer grade product, the Epoc X is sufficient for POCs but further investment into a research question, more less commercial hardware should be used. Given our limitations, it was decided that for this Thesis, the Emotiv Epoc X would be sufficient for our use case and based on the results, further financial investment would be made.

## 3.3 EEG Software

When deciding on which EEG software to use, we prioritize software that could integrate well with the Unity Game Engine. We needed the classification of user's intent to select an object to selection an object in the VE to have as little latency as possible. This is because eye tracking will be used for a hover state and if the classification is too delayed, the user could be looking at another object and accidentally select an object they didn’t mean to. At this point, we had already decided that we were going to use the Emotiv Epoc X as our EEG device and Emotiv already has software built to stream, clean and train the EEG data coming off their headsets. Using the EmotivBCI program, we were able to make “training profiles” to associate EEG data with a user and train the model on specific “mental commands.” The Emotiv Launcher handled authorization of our Unity programs' access to these training profiles and all the data associated with it. With most of the software development efforts of building our own classification model allievated, we could focus on integrating our Unity application with Emotiv’s Cortex API.

### 3.3.1 EMOTIVPRO

The EmotivPRO software handles the raw stream of EEG data coming from the Epoc X. This program doesn’t clean any of the data but it allows us access to all 14 channels on the headset for playback functionality. (See Figure #)

: EmotivPRO data stream playback from Emotiv Epoc X

### 3.3.2 EMOTIVBCI

#### 3.3.2.1 TRAINING DATA COLLECTION

#### 3.3.2.2 TRAINING PROFILES

Emotiv subscribers can make “training profiles” to associate EEG data with a user

## 3.4 NeuroGaze Software Architecture

### UNITY (Input and Display)

VR PLAYER RIG (META ALL IN ONE SDK)

INTERACTABLES

# CHAPTER FOUR: USER STUDY

## Results

QUANTATIVE

ACCURACY

PERCISION

RECALL

STAT ANALYSIS

ANOVA

WILCOXON

WILFRED

QUALITATIVE

After evaluating participants on all three input devices and

## Experimental Design

DATA COLLECTION

UNITY SCENE

INTERACTBLES

ASSESSMENT MANAGER

EXPORT TO CSV

TIME

ACCURACY

APPARATUS

NEUROGAZE

EYEGAZE AND HANDS

VR CONTROLLERS

EVALUATION SCENES

SRUVEYS

DEMOGRAPHICS

NASA TLXS

POST EVALUATION

## Implications

# CHAPTER FIVE: FUTURE WORK

# CHAPTER FIVE: CONCLUSION

# APPENDIX A: SAMPLE SURVEYS

## Qualtrics Demographic Survey

## Qualtrics NASA-TLX Survey

## Qualtrics Post Evalution Survey

[insert appendix content]

# LIST OF REFERENCES

*Below is a sample reference with a hanging indent, formatting along APA style.*

Allison, A. (2000). Japanese mothers and obentos: The lunch box as ideological state apparatus.   
In Permitted and Prohibited Desires: Mothers, Comics, and Censorship in Japan.   
Berkeley, CA: University of California Press, pp 81-103.