Implementing SSVEP-Objects for a Unity-based Simulation Program: Building and Verification

Project Work

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Abstract

This project focuses on developing a gamified task within a Virtual Reality (VR) Unity environment, integrating a Steady-State Visual Evoked Potential (SSVEP)-based Brain-Computer Interface. An interface is implemented to enable real-time communication between the Unity environment and the g.tec Unicorn Electroencephalogram (EEG) cap. To assess the feasibility and effectiveness of the approach, test measurements are performed that validate the performance of the system and its potential for practical applications. The results demonstrate promising potential for SSVEP-based BCIs in VR environments, though further improvements are necessary to address issues such as data quality, frame rate stability, and user comfort to fully realize the system's capabilities.

Declaration

I hereby declare that I have authored this work independently, that I have not used other than the declared sources and resources, and that I have explicitly marked all material which has been quoted either literally or by content from the used sources. This work has neither been submitted to any audit institution nor been published in its current form.

Saarbrücken, March 27, 2025

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1 Introduction

Brain-Computer Interfaces (BCI) are an increasingly popular alternative to traditional input devices like keyboards, mice, and touchscreens. One well-established BCI approach, described by Cheng et al. (2002) is based on Steady-State Visual Evoked Potentials (SSVEPs), which occur when the brain responds to repetitive visual stimuli, flashing at specific frequencies. By detecting these frequency-specific Electroencephalogram (EEG) responses, users can issue commands without any physical movement [1].

For instance, Nakanishi et al. (2014) proposed a high-speed SSVEP-based BCI spelling system that achieved a spelling rate of 40 characters per minute with high accuracy [2]. Recently Kanagaluru and Sasikala (2025) demonstrated high classification accuracies (up to 96.7%) using a single occipital EEG channel and machine learning techniques. This outperforms traditional multi-channel methods, highlighting the potential for simpler, more efficient systems [3].

SSVEP-based BCIs have transformative clinical applications as well. In rehabilitation medicine, they enable communication for individuals with severe motor impairments, such as those with locked-in syndrome (LIS) or amyotrophic lateral sclerosis (ALS). SSVEP-based spellers have demonstrated high accuracy, providing a practical communication method for LIS patients [4]. Shi et al. (2020) developed a calibration-free, asynchronous BCI system that allowed an ALS patient to achieve a free-spelling accuracy above 90%, with an information transfer rate exceeding 22 bits/min [5]. Furthermore, BCIs have been integrated with Functional Electrical Stimulation (FES) to assist motor recovery. Canny et al. (2023) proposed a combined BCI-FES system for locked-in individuals, enabling the restoration of facial expressions and limb movements, thereby enriching communication through body language [6].

BCIs using SSVEPs have been integrated with rehabilitation exoskeletons to assist stroke patients in regaining motor functions. By detecting SSVEP responses, these systems enable patients to control exoskeleton movements, facilitating active participation in their rehabilitation process. For instance, a study developed an augmented reality-based BCI system that combines SSVEP detection with an exoskeleton, enhancing the engagement and effectiveness of stroke rehabilitation exercises [7]. Gamifying the BCI task introduces an interactive element that transforms the traditionally clinical setup into a more engaging and immersive experience.

In gaming applications, immersion plays a pivotal role in enhancing user experience. It is a psychological state in which a user becomes deeply engaged and absorbed in a virtual or game environment, often described as a sense of "being there" within the environment. Jennett et al. (2008) define immersion as a continuum of experience, progressing through three stages: engagement, engrossment, and total immersion [8]. This sense of immersion is closely linked to the concept of flow, where individuals are fully absorbed in an activity [9].

Immersion is significantly impacted by the choice of controlling devices and traditional devices like keyboards and mice can disrupt immersion due to their physical and cognitive demands. In contrast, more intuitive interfaces, such as motion controllers, haptic feedback, and BCIs, enhance immersion by reducing cognitive load and seamlessly integrating with the virtual environment, as discussed by Jennett et al. (2008) [8].

This project aims to bridge these domains by developing an immersive VR game using BCI where the game controls are done solely through SSVEP-based commands. The task of the participants playing the game is to control a character through a procedurally generated maze. The system integrates the g.tec Unicorn EEG cap with a Simulink-based signal processing and classification pipeline. A machine learning model, trained on EEG data acquired during the calibration procedure, classifies SSVEP responses as game controls. The Meta Quest II VR headset is used to present the virtual environment. The effectiveness of the system is evaluated through test measurements to assess its accuracy and feasibility for non-invasive BCI-based gaming applications.

2 Project Objectives and Goals

Traditional VR games rely on controllers or motion tracking for user interaction, making them inaccessible to people with severe motor impairments. This project aims to bridge this gap by implementing an SSVEP-controlled interface for VR navigation, assessing its effectiveness while also eliminating the need for hand controllers for games and applications with simplistic controls. The primary challenges include the following:

- Designing a robust SSVEP stimulus presentation system within the virtual environment and confirming that the presented frequency of the SSVEP object matches its desired programmed frequency.

- Minimizing the delay of the EEG data processing and command classification, while simultaneously maximizing the classifier accuracy and preprocessing resolution. Proper balance is essential for making the paradigm feel responsive to the participant, thus increasing immersion in the virtual environment and focus on the given task, while decreasing irritability and frustration.

- Training and integration of an effective machine learning classifier to distinguish between different SSVEP-induced EEG patterns.

The project objectives are as follows:

1. **Develop a VR-based game in Unity**, where movement is controlled solely through SSVEPs.

2. **Implement a calibration procedure** to collect EEG data for model training and signal quality monitoring.

3. **Train a K-Nearest Neighbors (KNN) model** in Simulink for real-time classification of commands.

4. **Evaluate the system's classification accuracy and usability of the system classification** through experimental tests with participants.

3 Materials and Methods

3.1 Materials

The hardware used in this study consisted of several key components for both EEG signal acquisition and the execution of the VR game. The EEG signals were recorded using the **g.tec Unicorn Hybrid Black EEG cap**, an 8-channel hybrid electrode EEG system, shown in Figure 3.1. Additionally, the **Meta Quest II** VR headset (Figure 3.2) was used for presenting the virtual environment to the participants.

The software used in this project included several essential tools for signal processing, game development, and device management. The VR game, designed for SSVEP stimulus presentation, was developed in **Unity 6**. EEG signal processing, feature extraction, and classification using machine learning were performed with **MATLAB/Simulink R2024a**, ensuring efficient data handling and real-time analysis. The **Unicorn Suite Hybrid Black** software facilitated the connection and management of the g.tec Unicorn EEG cap, while **Meta Quest Link** software was used to manage the connection between the Meta Quest II headset and the computer.

Figure 3.1: The g.tec Unicorn Hybrid Black EEG cap.
[10]

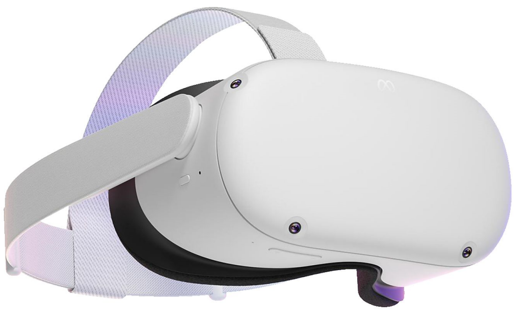

Figure 3.2: The Meta Quest II VR headset.
[11]

3.2 Methods

The EEG signals acquired using the g.tec Unicorn EEG cap are sent to the EEG signal processing computer using Bluetooth. The eight electrodes of the Unicorn Hybrid Black are: Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8, according to the international 10-20 electrode placement system [12]. Only the EEG Channel Oz is used for further processing and command classification. The mastoids serve as the reference electrodes. Electrodes were fitted with gel to ensure lower impedance and higher resistance to noise during the measurement. The EEG cap has a sampling frequency of 250 Hz, which is accounted for in the EEG processing pipeline within Simulink.

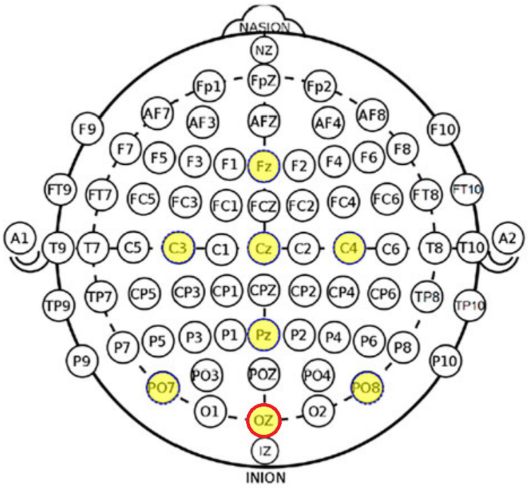

Figure 3.3: The 10-20 electrode placement system, with electrode positions of the system highlighted in yellow and the used electrode marked with a red circle. The ground and reference electrodes are attached to the mastoids using disposable sticker-based surface electrodes and are not shown in the graphic. [12]

The game was developed as a 3D Unity project utilizing the Universal Render Pipeline and includes three distinct scenes: a Main Menu, a Calibration scene, and a Game scene. Once the core structure of the game was implemented, VR compatibility was added.

The Main Menu provides users with an intuitive interface for navigating between the different scenes of the project. This menu ensures that the Unity project remains organized and coherent throughout the various phases of the measurement process. Additionally sound effects were added to the game for the menu options scrolling, the selection of a menu option as well as a separate sound, played when a collectible object is picked up. This serves as an auditory feedback, complementing the visual feedback from the game and improving immersion.

Figure 3.4: The Main Menu of the game, which allows users to easily navigate between the different scenes.

An Options Menu was also integrated into the game, providing flexibility by allowing users to adjust key parameters in real-time during the measurement process. This includes the ability to change individual stimulus frequencies, modify calibration settings, and adjust the User Datagram Protocol (UDP) communication parameters. These dynamic adjustments can be made without needing to rebuild the Unity project, saving valuable time and affecting the player's interest and irritability for the measurement.

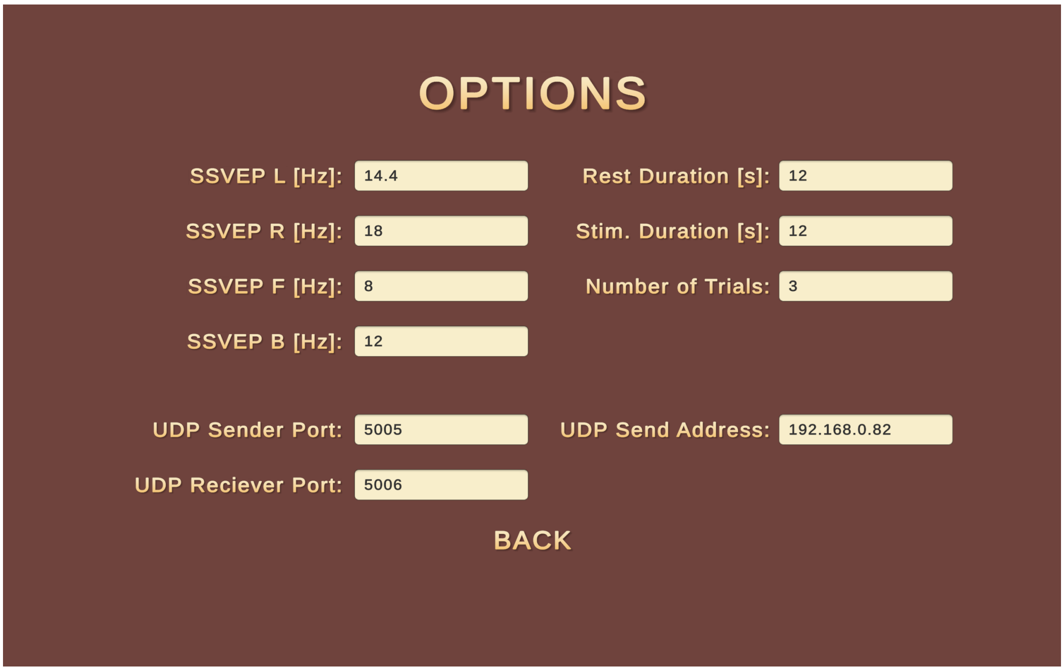

Figure 3.5: The Options Menu, which includes the following parameters: SSVEP L [Hz], SSVEP R [Hz], SSVEP F [Hz], and SSVEP B [Hz], which define the stimulation frequencies for left, right, forward, and backward commands, respectively. Rest Duration [s] specifies the length of rest periods between stimulus presentations, while Stim. Duration [s] indicates the duration of each stimulus. The Number of Trials determines the number of calibration trials per class. The UDP Sender Port and Receiver Port configure the ports used for data transmission, and the UDP Send Address specifies the target IP address for transmitting the data.

3.2.1 Calibration

Before gameplay, a calibration sequence is used by accessing the 'calibration' option from the main menu as shown in Figure 3.6. A single SSVEP object presents each stimulus frequency consecutively, where each stimulus corresponds to a direction of movement. The g.tec Unicorn EEG cap records EEG signals while the player focuses on each stimulus. Unity sends labeled data (indicating the active stimulus) to Simulink via UDP as shown in Figure 3.8. The value `8` is used as a start of the calibration procedure and the value `9` as the end of the calibration procedure. Simulink extracts frequency-domain features using a Fast Fourier Transform (FFT) with a window applied to the temporal-domain data of 1000 samples and 250 samples overlap, to prevent abrupt frequency changes between two consecutive windows. The Fourier Transform is passed onto a Complex to Magnitude-Angle block from which only the magnitude is processed further to calculate the data features. Bins with width of 2 Hz ($\pm$1 Hz) are calculated, centered at each stimulation frequency (8 Hz, 12 Hz, 14.4 Hz, and 18 Hz) as well as at their respective first harmonics (16 Hz, 24 Hz, 28.8 Hz, and 36 Hz).

These frequencies were selected based on the VR headset's recommended refresh rate of 72 Hz. During measurements, the VR headset was set to that recommended refresh rate. To ensure proper stimulus presentation without screen tearing, the selected frequencies must be integer multiples of the headset's refresh rate [13]. Thus stimulus frequencies were chosen to be integer multiples of this refresh rate and were also spaced sufficiently apart to prevent overlap between the frequency bins used.

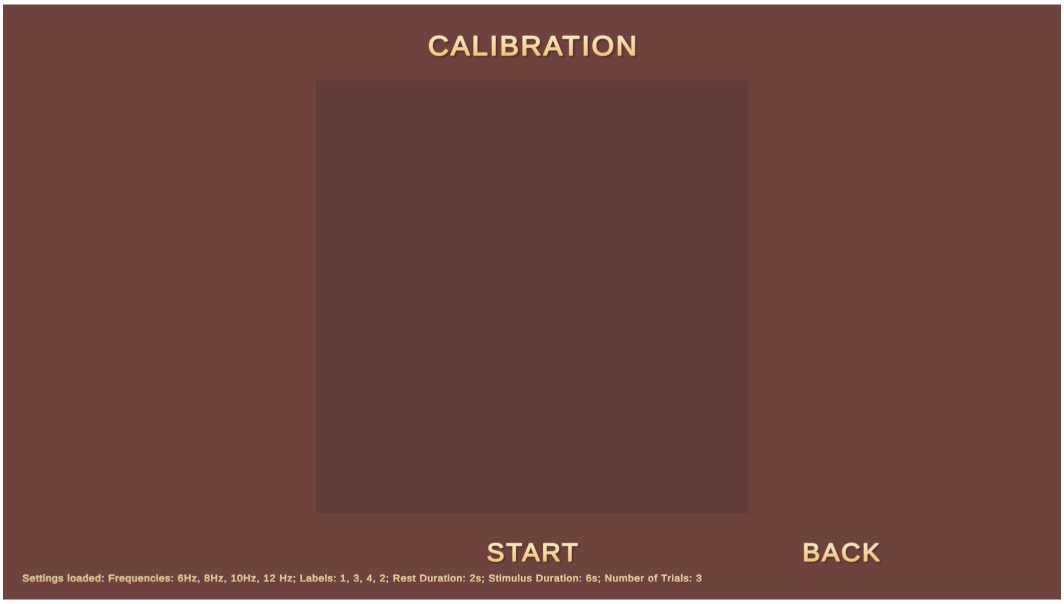

Figure 3.6: The Calibration Menu of the game.

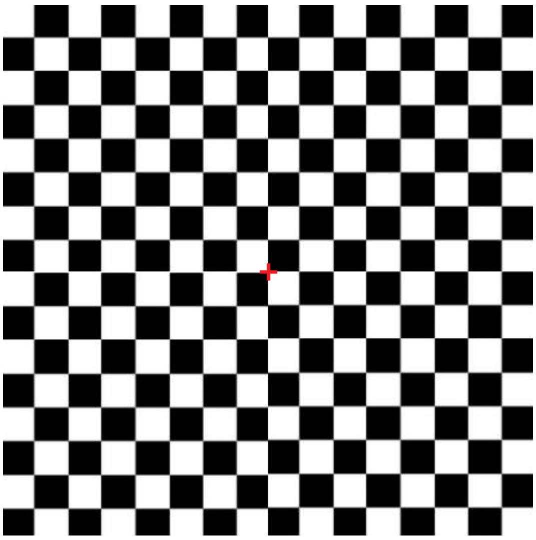

Figure 3.7: The SSVEP Stimulus.

The SSVEP stimulus used in this project is an alternating black and white square with checkerboard pattern and a red cross in the middle, shown in Figure 3.7, which was added during testing as it helped keep the participant's focus and attention in the middle of the stimulus. As described by Zhu et al. (2021) a high contrast difference is necessary for the effectiveness of the SSVEP stimulus [14]. The black and white checkerboard pattern proved to be a really good stimulus, thus different hues and saturation combinations were not tested.

The checkerboard pattern was chosen over flash flickering stimuli because it provides a better balance between performance and user comfort. As described by Reitelbach et al. (2024) flash flickering can elicit stronger SSVEP responses, but it tends to cause more visual fatigue and discomfort [15]. The checkerboard's alternating tiles create a higher spatial frequency, enhancing signal quality without excessive luminance contrast, making it more sustainable for prolonged use.

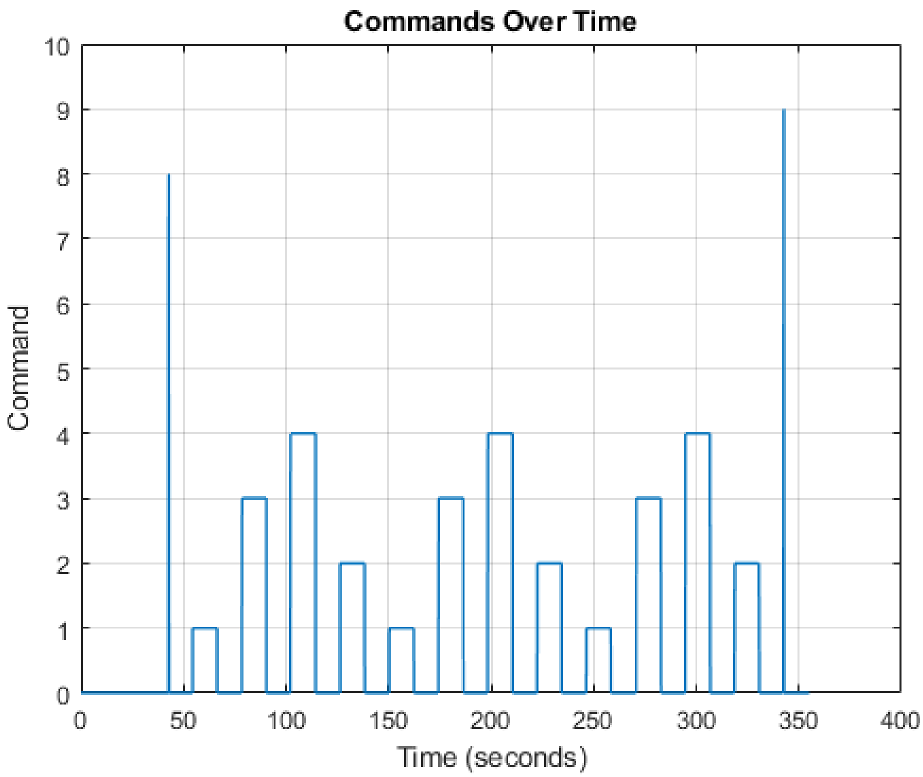

Figure 3.8: The Commands corresponding to the SSVEP-Stimuli, with their mapping as follows: mapping: 0=No movement (no stimulus), 1=Up (8 Hz), 2=Down (12 Hz), 3=Left (14.4 Hz), 4=Right (18 Hz)

The calibration measurement consists of three trials per class, beginning with a 12-second rest period, during which a black rectangle with a red cross at its center is displayed.

Following this, a visual stimulus is presented for 12 seconds. This sequence is repeated for each of the four stimulus frequencies in the order: 1 (Up, 8 Hz), 3 (Left, 14.4 Hz), 4 (Right, 18 Hz), and 2 (Down, 12 Hz) three times, resulting in a total of 12 stimulus trials. This ensures sufficient training data for classifier training while maintaining low visual fatigue of the participant. In order to generate a labeled dataset for training and testing of the KNN model each trial's class label is processed together with each corresponding FFT window to extract the data labels.

The parameter values used are as follows:

- Stimulus Duration: 12 seconds
- Rest Period Duration: 12 seconds
- Number of Calibration Trials per class: 3

3.2.2 Feature Extraction and Model Training

After the calibration phase, the recorded EEG data is processed in MATLAB to extract relevant features for classification. The EEG signals are first preprocessed using a bandpass filter (5–40 Hz) of order 1000 to remove unwanted frequency components. This is achieved using the built-in MATLAB function `fir1`. The signals are then segmented into overlapping windows of 1000 samples (4 seconds) with a 250-sample overlap. For each window, the magnitude of the FFT is computed, and frequency bins corresponding to the four SSVEP stimulation frequencies: 8 Hz, 12 Hz, 14.4 Hz, and 18 Hz are summed, following the approach described in Volosyak et al. (2011) [16]. This is done to process the EEG data in the same way that the Simulink pipeline (Figure 3.11) is processing the real-time data. Additionally, the first harmonic (twice the stimulation frequency) is computed, and the ratio between the fundamental and harmonic magnitudes is calculated. To include rest periods as a feature, we introduced an additional metric by multiplying the first two frequency bins (8 Hz and 12 Hz) and dividing by the product of the next two bins (14.4 Hz and 18 Hz). This feature helps distinguish between stimulus-present and stimulus-absent states by capturing their frequency relationships. These values are compiled into a feature table, containing a total of 13 features, with each row representing a single window and its corresponding class label. The extracted features are then used to train a classification model. Through tests using collected calibration measurement data the KNN model, with K = 10 neighbors proved to be best suited for the goal of this project, similar to İşcan et al. (2018) [17]. It outperformed other Simulink supported models in training and testing accuracy consistently. Once the optimal model was selected, it was exported from to the Simulink model shown in Figure 3.11 as a trained classifier block for real-time EEG signal classification during gameplay.

```
Feature extraction complete. Classes before balancing:
    Label     GroupCount     Percent
    _____     __________     _______

      0          102         51.256 
      1           24          12.06 
      2           24          12.06 
      3           24          12.06 
      4           25         12.563 

Classes after balancing:
    Label     GroupCount     Percent
    _____     __________     _______

      0           24           20   
      1           24           20   
      2           24           20   
      3           24           20   
      4           24           20   

Feature extraction complete. Data saved to eeg_features.mat
Iteration 1 Accuracy: 95.83%
Average Classifier Accuracy over 1 runs: 95.83%
Classifier retrained with full feature table.
```

Figure 3.9: Class balance before and after processing.

The collected data exhibited class imbalance, meaning some classes were overrepresented while others were underrepresented, as can be seen in Figure 3.9. This caused the classifier to misclassify commands and label them as 0, due to the higher occurrence of that class in the training data. To address this, class balancing techniques were applied to ensure a more even distribution of samples across all classes, improving the model's ability to generalize.

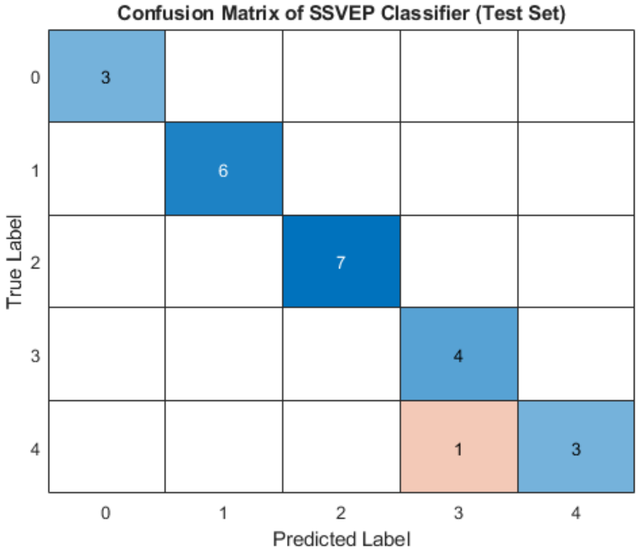

Figure 3.10: Confusion Matrix of the trained KNN classification model. Frequency-label mapping: 0=No movement (no stimulus), 1=Up (8 Hz), 2=Down (12 Hz), 3=Left (14.4 Hz), 4=Right (18 Hz).

A confusion matrix shown in Figure 3.10 is a table that visualizes an algorithm's classification performance by comparing predicted labels against true labels. Each column represents actual classes, while rows show predicted classes. It highlights correct and incorrect predictions, and from it we can identify specific misclassification patterns. It is helpful for supervision of the model's performance through changes and iterations in the Simulink feature processing pipeline.

The classifier's accuracy is determined as follows: During data processing, 13 feature columns are stored alongside a 14th column containing the class labels. Each row represents a processed FFT window from the calibration measurement. Once the full dataset is processed and class balancing is applied, the table rows are shuffled, with the top 80% of the table used for training and the bottom 20% is set aside for testing. The accuracy score is then computed as the ratio of correct predictions to the total number of test samples.

3.2.3 Simulink Model for Real-Time EEG Processing and Classification

The Simulink model processes real-time EEG data recorded via the Unicorn Hybrid Black EEG headset and classifies it using the KNN model trained on the data acquired during calibration. The pipeline consists of several key stages.

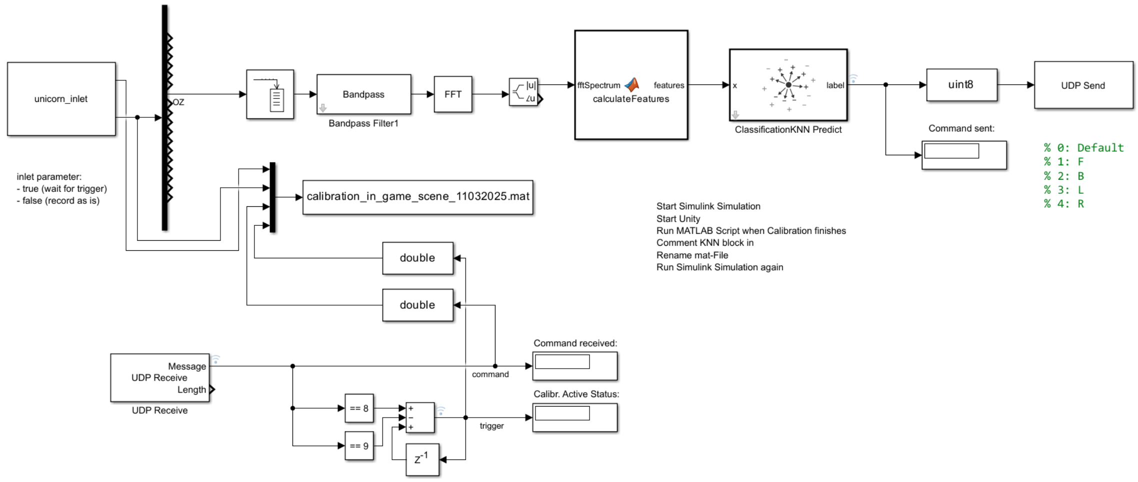

Figure 3.11: The Simulink Pipeline.

EEG Data Acquisition The `unicorn_inlet` block receives the EEG signals for all electrodes. Data is stored as a `.mat` file and can be processed in real-time or offline using recorded calibration data.

Preprocessing and Feature Extraction A De-multiplexer block is used to extract only the Oz channel for further processing. The `Buffer` block receives the Oz channel signal and buffers it in a window of 1000 samples with 250 samples overlap. With the 250 Hz sampling frequency of the EEG cap this corresponds to a 4 second window with 1 second overlap. Each window passes through a bandpass filter (5–40 Hz) to remove power line noise and low-frequency physiological artifacts. In Figure 3.12 an FFT of a calibration measurement data can be seen. An FFT block computes the FFT spectrum of the window, essentially creating a Short-Time Fourier Transform (STFT) for real time data for the calibration measurement processed after the measurement, and a `Complex to Magnitude-Angle` block extracts magnitude spectrum of the filtered signal, which is then passed to the custom MATLAB function block `calculateFeatures`. The block normalizes the spectrum by its peak magnitude before isolating the frequency bins matching SSVEP stimulation frequencies (8 Hz, 12 Hz, 14.4 Hz, 18 Hz) and their first harmonics (16 Hz, 24 Hz, 28.8 Hz, and 36 Hz) as well as the ratios between the stimulation frequencies and their harmonics. The exact same pipeline is used as a MATLAB script to train the KNN model on the 13 chosen features and load it from the MATLAB Workspace to the respective Simulink Block for live classification. For the classifier training the Simulink simulation needs to be stopped and started again after the model is successfully trained.

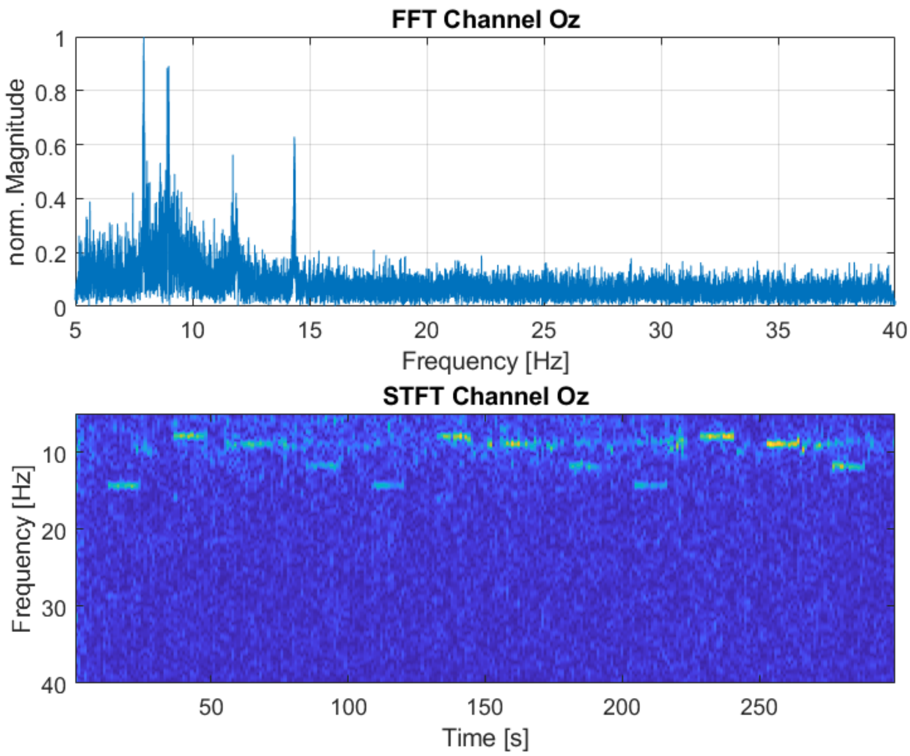

Figure 3.12: The FFT and STFT of the calibration measurement during development.

Classification and Command Selection After the KNN classifier is trained and the simulation is started again the extracted live features are passed to the trained machine learning model for classification. During gameplay, the model classifies real-time EEG input, outputting a control command `uint8` representing movement directions:

- 0 $\rightarrow$ Default (No movement)
- 1 $\rightarrow$ Up
- 2 $\rightarrow$ Down
- 3 $\rightarrow$ Left
- 4 $\rightarrow$ Right

The command 0 is necessary so that the classifier does not send movement commands to the game even when the player is not actively looking at a stimulus object. This ensures that the player must focus on the SSVEP stimulus in order to trigger a command.

A Sample and Hold (S/H) block ensures stable command transmission.

UDP Communication Commands are sent to the game, where they control the character's movement in the VR maze. For that a UDP connection is set up, using the Internet Protocol version 4 (IPv4) address of the computer as a source and a destination Internet Protocol (IP), so that the information can be exchanged between the different software programs locally.

3.2.4 Gameplay and SSVEP-Based Navigation

The player controls a character, the open source Jammo robot asset, which moves through a maze to collect randomly placed collectible objects (bolts) [18, 19]. For the consistent generation of a solvable maze a recursive backtracking algorithm is implemented. A new maze starting from the character's position is generated each time the game starts and when a collectible object is acquired respectively. Four SSVEP stimuli are displayed on the outer walls of the maze, corresponding to the relative movement directions, as shown in Figure 3.13. This stimuli placement is used by Güneysu et al. (2013) , Wong et al. (2015) as well as Shao et al. (2020) and was chosen for this project due to its intuitive nature and ease for control by the player [20, 21, 22].

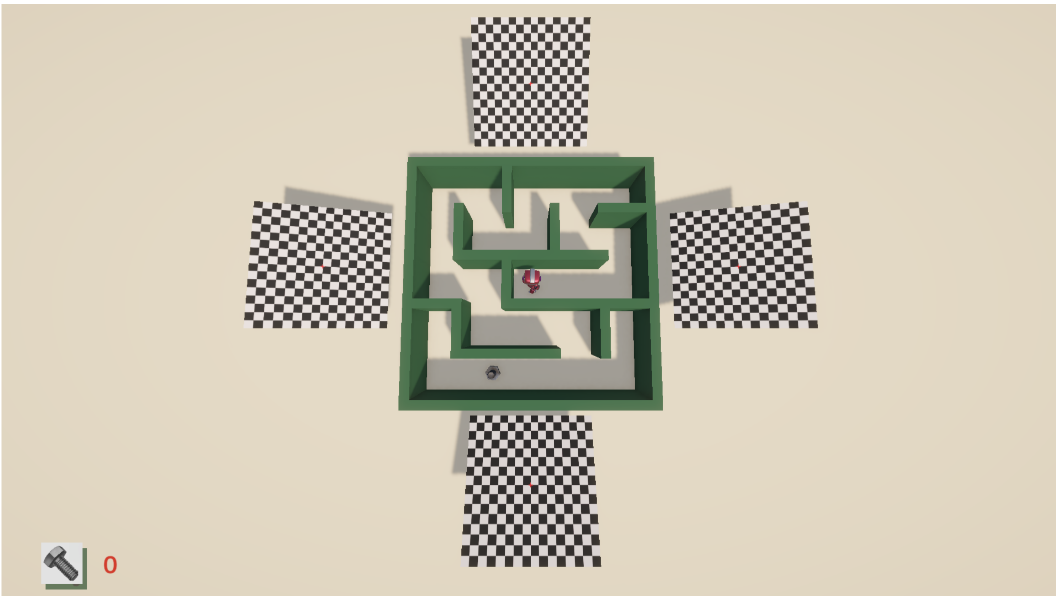

Figure 3.13: The Game Layout, containing the stimuli close to the center to minimize movement artifacts in the EEG data.

The system maps directional commands based on the participant's perspective (Up, Left, Right, Down) to SSVEP stimuli, where EEG responses to the stimuli are processed and classified into uint8 movement commands transmitted via UDP to the game. In Unity, each received command triggers the corresponding movement of the robot based on its current orientation, executing the action for 0.5 seconds. If the received command is 0, no action is performed.

To assess user experience, post-experiment questionnaires were adapted from immersion scales used by Jennett et al. (2008), utilizing a 5-point Likert system (1 = strongly disagree, 5 = strongly agree) [8]. The aim of the questionnaires was to gather participants' subjective feedback on various aspects of the experiment, including their focus, immersion, and perception of the system. These insights helped evaluate the effectiveness of the experimental setup and the overall user experience.

4 Results

The SSVEP-based BCI system's performance was assessed through experimental trials involving two participants. Evaluation metrics focused on three key aspects: classification accuracy, in-game performance, and subjective feedback collected via questionnaire.

Classification accuracy was 58.33% for the calibration measurement of the first participant and 66.67% for the second participant. Analysis of the FFT and STFT spectra of the acquired data revealed significant inconsistency between calibration measurements of the two participants. The results can be seen in Figures 4.1 and 4.2. This technical inconsistency contributed in the gameplay phase of the measurement - despite concentrated effort, neither participant successfully collected any bolts during the task.

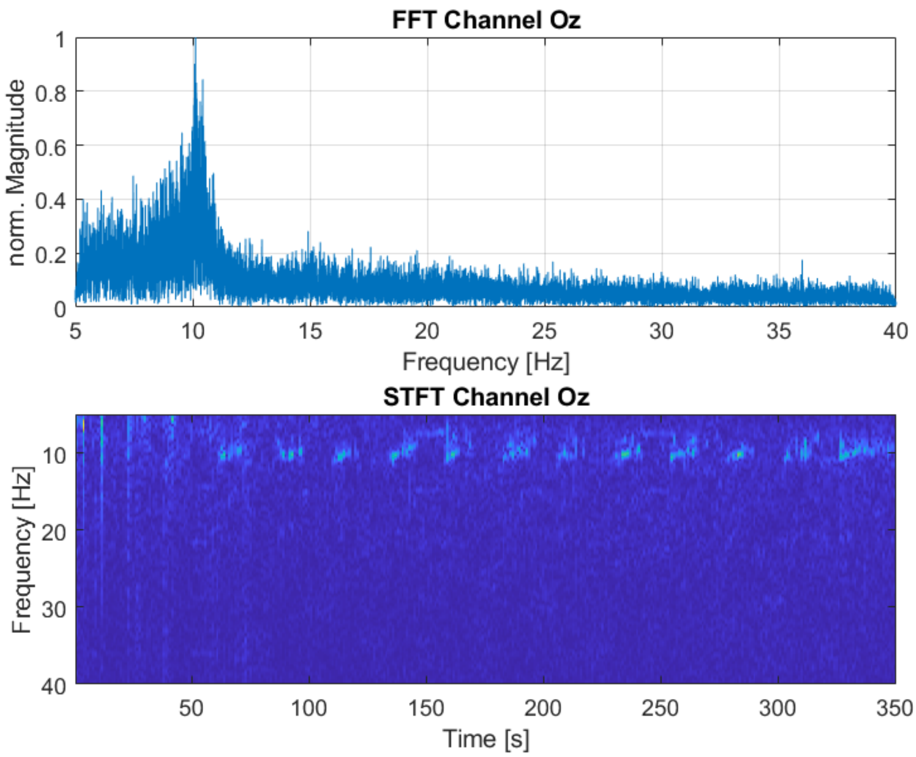

Figure 4.1: The FFT and STFT of the calibration measurement of first participant.

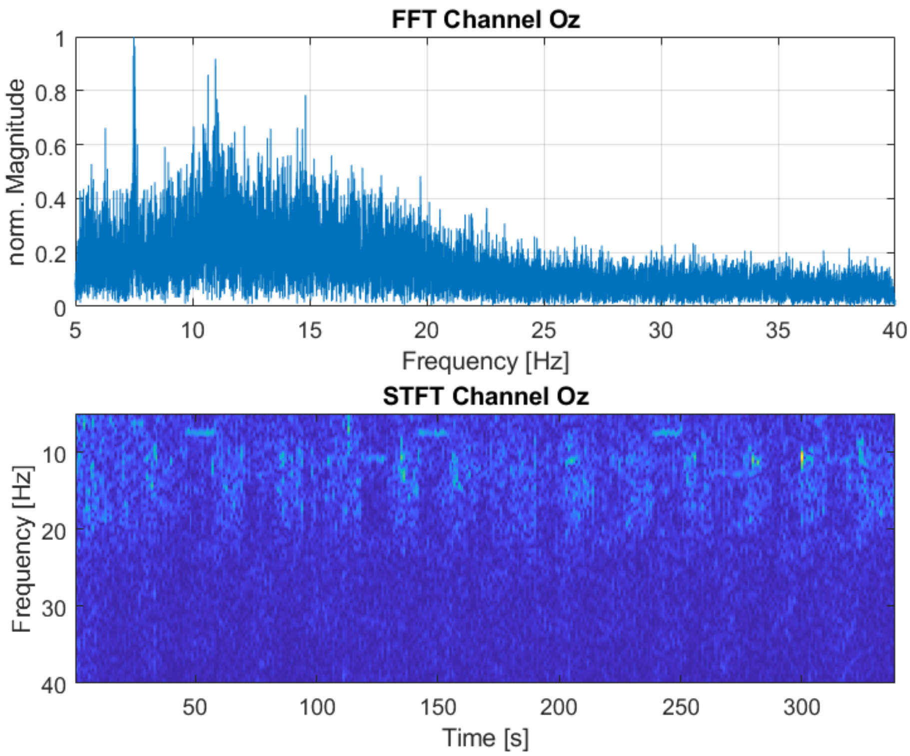

Figure 4.2: The FFT and STFT of the calibration measurement of second participant.

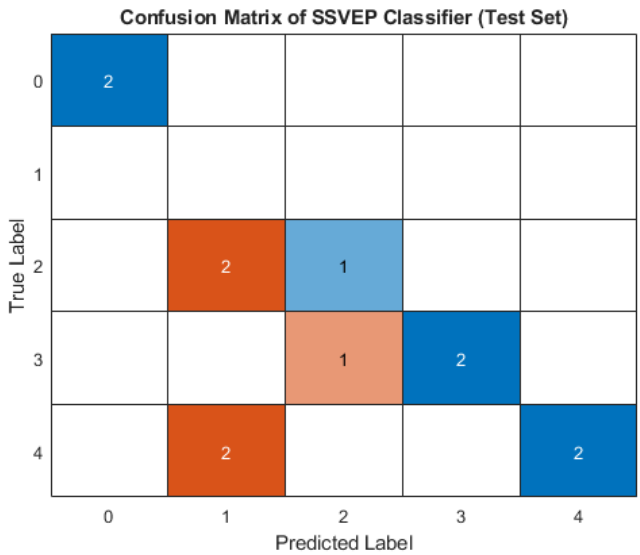

Figure 4.3: The confusion matrix of the first participant.

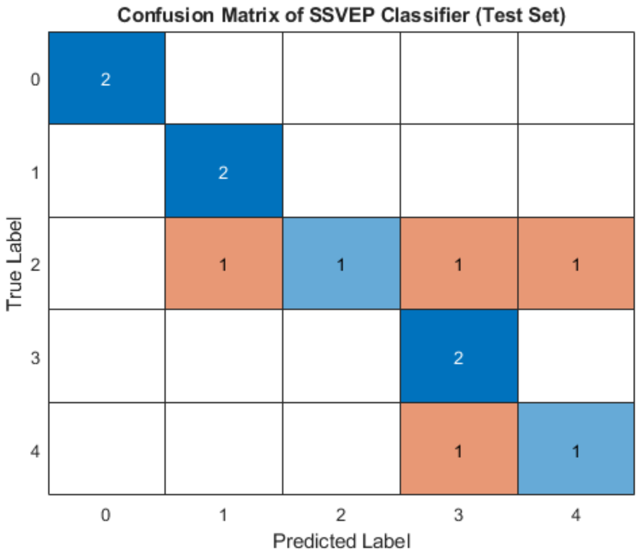

Figure 4.4: The confusion matrix of the second participant.

The results of the post-experiment questionnaire provided insights into user experience, immersion, and interaction with the BCI system, while also highlighting specific issues with control intuitiveness. Both participants reported relatively high focus on the game (4/5), suggesting engagement despite the lack of successful in-game task completion. Both subjects disagreed with the statement that there were no frustrating aspects of the controls, confirming the impact of the low classifier accuracy on user experience. Furthermore, when asked whether they felt as though they were moving through the game according to their own will, participants gave slightly different answers, but both were low (1/5 and 3/5). Despite the system's limitations however, both participants strongly agreed (5/5) that they did not feel the urge to stop playing and check their surroundings, suggesting that, while imperfect, the VR-based task was sufficiently engaging to maintain attention. Interestingly, the participants also reported a different degree of losing track of time (2/5 and 4/5), hinting at individual differences in temporal perception while using the system.

An additional control measurement was done with the second participant, this time without the VR headset, but displaying the game on the screen of the data acquisition computer. Below the FFT and STFT data plots can be seen in Figure 4.5, as well as the confusion matrix of the classifier in Figure 4.6. The classifier test accuracy for this measurement was at 91.67%. In the second measurement the participant was able to collect a total of 2 bolts during the task, while also exhibiting a much greater ability to control the in-game character. This demonstrated the feasibility of the SSVEP-based BCI approach, although it was unsuccessful in the VR environment.

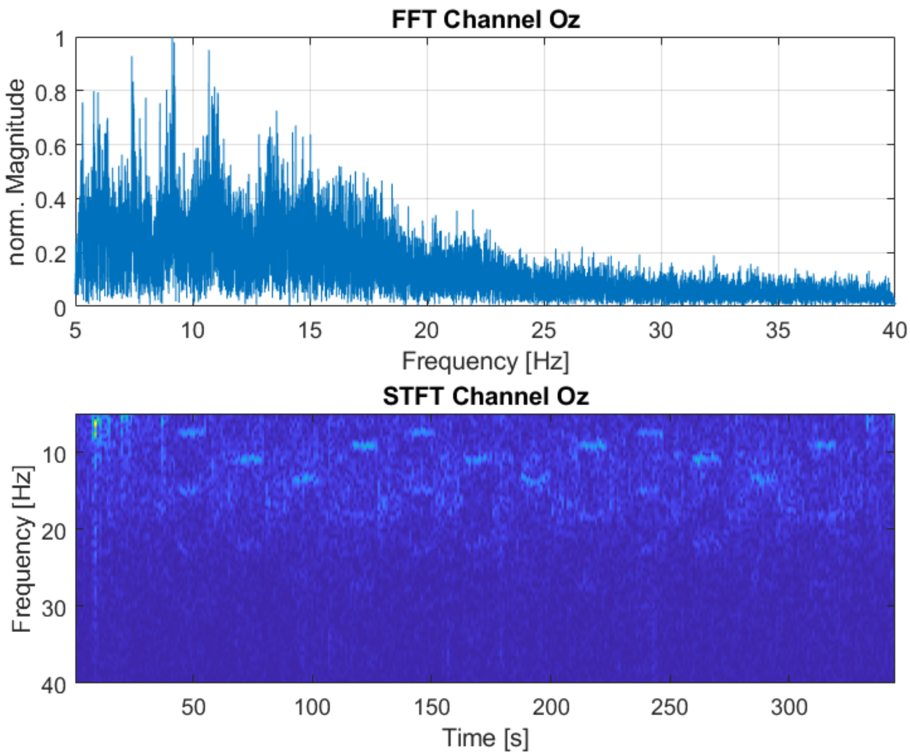

Figure 4.5: The FFT and STFT of the calibration measurement of second participant during the measurement without the VR headset.

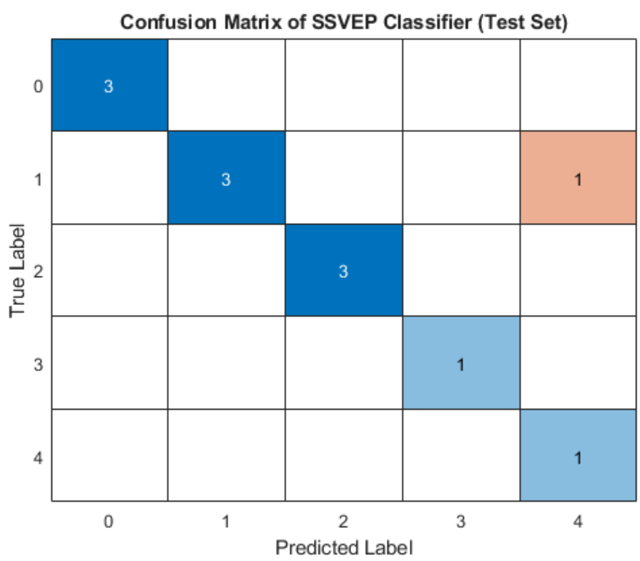

Figure 4.6: The confusion matrix of second participant during the measurement without the VR headset.

This additional measurement demonstrated that the SSVEP-based BCI approach is feasible in a non-VR setting, as the participant achieved a high classifier accuracy while also successfully controlling the in-game character. However, the lack of success in the VR condition suggests that specific factors hindered its effectiveness. Rather than disproving the feasibility of SSVEP-based BCI in VR, these results indicate that modifications are necessary to make it viable. Some of the key adjustments include improving EEG signal stability, addressing potential interference from the VR headset, and ensuring precise flickering frequencies. A possible workaround could involve external hardware to generate stable visual stimuli, independent of Unity's frame rate fluctuations. This measurement confirmed that the core BCI system functions under controlled conditions, highlighting the need to refine the VR implementation to overcome the observed challenges.

5 Discussion

The goal of this project was to evaluate the feasibility of an SSVEP-based BCI for a gamified task within a VR Unity environment. However, data quality issues significantly impacted the effectiveness of the system, limiting its performance.

Several factors may have influenced data quality. One key issue was the weight of the VR headset, as the imbalanced weight distribution on the participant's head strains the neck muscles, which could lead to muscle artifacts in the Oz channel.

Another possible factor could be the inconsistency of the frame rate of the game. A frame rate manager was implemented with a target frame rate set at 72 Hz, which is the default and recommended refresh rate of the VR headset used. However, there were noticeable fluctuations in the actual frame rate, ranging from 63 Hz to 95 Hz. For instance, when the refresh rate reached 95 Hz, this resulted in a 31.94% disparity compared to the target 72 Hz. Since the stimulation frequencies must be integer multiples of the refresh rate to ensure accurate stimulus presentation without screen tearing, this variation in the refresh rate can cause discrepancies in the frequencies displayed, as described by Oralhan (2016) [13]. Such jitter or fluctuation in the refresh rate introduces additional challenges, potentially displacing the FFT peaks in the acquired data and leading to inaccurate or inconsistent stimulation, thereby affecting the prediction of the KNN classifier and thus the participant's ability to control the in-game character.

Furthermore, no option was found to lock the frame rate at the specified frequency. In Unity, `Application.targetFrameRate` sets a desired frame rate but does not strictly enforce it due to factors such as platform limitations, hardware performance, and VSync (Vertical Synchronization), which synchronizes the game's frame rate with the monitor's refresh rate to prevent screen tearing and ensure smooth visual output. For SSVEP-based BCIs, VSync is typically disabled to ensure precise flickering at the target stimulation frequency. In this project, it was similarly disabled to maintain accurate stimulus presentation. This is because VSync can introduce timing inconsistencies by forcing synchronization with the display's refresh cycle, potentially reducing flicker accuracy and interfering with the intended stimulation rate. A study by Faller et al. (2010) demonstrated that enabling VSync can limit the available range of flicker frequencies for stimulation [23]. Additionally, VSync can disrupt stimulation pattern rendering, particularly in systems using DirectX, an Application Programming Interface (API) that provides direct access to the graphics card. In such systems, disabling VSync is essential to prevent disruptions in the graphics device interface, as highlighted by Olze et al. (2017) [24].

Another possible reason for this could be the electromagnetic interference (EMI) or electromagnetic compatibility (EMC) radiation emitted by the VR headset, which may affect the sensitive EEG electrodes placed in close proximity, potentially leading to noise or distortion in the recorded EEG data. No information was found on the Meta Quest II regarding specific EMI peaks or their impact on EEG signals.

Additional challenges include the inability to monitor electrode impedances, making gel application and electrode placement uncertain, especially during the placement of the VR headset, which may displace electrodes or alter their pressure. Mahmood et al. (2022) developed flexible, wearable EEG systems with soft, stretchable interconnectors and dry needle electrodes, which can enhance user comfort while also maintaining electrode positioning. Their system is successfully integrated with VR headsets to enable monitoring for portable and wireless BCI applications, neurological rehabilitation, and disease diagnosis [25].

The effectiveness of SSVEPs is notably influenced by individual differences among participants. Variations in neural responses to visual stimuli can lead to significant differences in BCI performance, as shown by to İşcan et al. (2018) [17]. Additionally, factors such as age, attention levels, and cognitive load have been shown to affect SSVEP responses, further contributing to the subjective nature of BCI performance [17]. Therefore, tailoring BCI systems to accommodate these individual differences is crucial for enhancing their reliability and effectiveness. For instance, a study by Vialatte et al. (2010) investigated SSVEP responses across a range of frequencies (5–30 Hz) in ten subjects and found considerable inter-subject variability in the magnitude and frequency tuning of SSVEPs [26]. This variability highlights the need for personalized calibration of stimulation frequencies to optimize BCI accuracy for each user. A potential future improvement could involve analyzing the standard deviation of the detected SSVEP peaks relative to the stimulus frequencies and adjusting the FFT bins accordingly. By shifting the frequency bins to align more closely with the participant's actual perceived frequencies, the system could better capture SSVEP responses during calibration, potentially improving classification accuracy.

Integrating SSVEP-based BCIs with VR environments presents several challenges, as evidenced by prior research. Studies have explored the combination of VR headsets with EEG caps, aiming to enhance BCI applications. For instance, a study by Larsen et al. (2024) developed a synchronized method for using EEG and eye tracking in fully immersive VR, highlighting the importance of precise synchronization between EEG data and VR stimuli that is subjective to each participant to ensure accurate SSVEP detection [27].

The questionnaire responses suggest that, despite its technical limitations, the BCI system successfully maintained user focus and engagement, as both participants strongly agreed that they did not feel the urge to disengage from the task (5/5). However, the moderate immersion scores indicate that technical inconsistencies, particularly in control accuracy, negatively impacted the overall user experience. Furthermore the disparity between the participants in responses regarding losing track of time (2/5 and 4/5) highlights individual variability in immersion, aligning with prior studies on SSVEP-based BCIs, where variations in neural responsiveness influence usability and user experience [17]. Studies by Diez et al. (2011) observed that high-frequencies SSVEP produce much less visual fatigue than lower frequencies and the study findings of Ladouce et al. (2022) suggest that lower amplitude stimuli can enhance visual comfort without compromising system performance, addressing concerns related to visual fatigue and discomfort during prolonged use [28, 29]. Future developments could explore modifications to these stimulus characteristics to assess their impact on user experience and determine any potential trade-offs in the quality of the recorded data.

The results underline the need for system improvements, particularly in enhancing classifier accuracy to provide users with more precise and intuitive control. The development of an automated calibration pipeline could further improve system performance, as the existing calibration and classifier training process requires interrupting the simulation to load the trained model. Implementing dynamic calibration data processing and model training would significantly reduce setup time while improving both immersion and user-friendliness. User comfort could be further enhanced by addressing fatigue through alternative stimulus designs. Another priority includes the pipeline's capability of handling muscle artifacts and implementing precise frame rate control.

6 Conclusions and Future Work

This project demonstrated the potential and challenges of implementing an SSVEP-based BCI system within a VR environment. While the system showed promise, several areas require improvement to enhance its performance and reliability.

A key factor limiting the system's performance was the frame rate inconsistency of the VR application. Although the game was designed with a target frame rate of 72 Hz, significant fluctuations were observed, ranging from 63 Hz to 95 Hz, which is due to the inability to lock the frame rate within Unity. However, ensuring a more stable and consistent frame rate would improve the accuracy of the system's visual stimulus presentation, ultimately leading to better SSVEP responses.

User comfort is another critical area for enhancement. As discussed, the weight of the VR headset and the potential for neck strain can cause muscle artifacts, particularly in the Oz channel. The questionnaire results also highlighted that both participants found the controls frustrating, which may have been influenced by these physical discomforts and the difficulty in achieving precise control. Incorporating lighter and more ergonomic designs for headsets, or integrating flexible EEG systems as suggested by Mahmood et al. (2022), could reduce physical discomfort and prevent electrode displacement. Furthermore, real-time impedance monitoring would ensure the accuracy and stability of the electrode signals, providing more consistent data during extended sessions.

Finally, the individual variability in SSVEP responses highlighted the need for more personalized BCI solutions. Factors such as neural responses, attention levels, and cognitive load contribute to significant performance differences. Adapting the system's calibration process to account for these individual differences would improve its adaptability and effectiveness. Future work could explore methods to automatically adjust stimulation frequencies based on real-time feedback from the user's neural responses, improving the overall BCI experience.

In summary, while the current system demonstrates the feasibility of an SSVEP-based BCI in VR, addressing the challenges of calibration, frame rate consistency, electrode placement, and user-specific factors will be essential for advancing the technology. By focusing on these areas of improvement, future developments could lead to more reliable, comfortable, and effective VR-based BCI systems.

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List of Abbreviations

ALS Amyotrophic Lateral Sclerosis (ALS) is a progressive neurodegenerative disease that affects nerve cells in the brain and spinal cord, leading to muscle weakness and loss of voluntary muscle control. . 4

API An Application Programming Interface (API) is a set of rules and protocols that allows one software application to interact with another, enabling integration and communication between systems.. 26

BCI A Brain-Computer Interface (BCI) is a system that enables direct communication between the brain and an external device, typically by interpreting neural signals to control applications such as prosthetics, communication aids, or gaming. 4

EEG The Electroencephalogram is a weak bioelectric signal originating from the electric sum activity of the apical dendrites of pyramidal neurons in the neocortex. 1, 4

EMC Electromagnetic compatibility (EMC) is the ability of electronic devices to operate without causing or being affected by electromagnetic interference.. 27

EMI Electromagnetic interference (EMI) refers to the disruption or distortion of an electronic signal caused by electromagnetic radiation emitted from external sources that can affect the performance of electronic devices, including EEG systems.. 27

FES Functional Electrical Stimulation (FES) is a therapeutic technique that uses low-energy electrical pulses to artificially generate body movements in individuals who have been paralyzed due to injury to the central nervous system.. 4

FFT The Fast Fourier Transform (FFT) is an efficient algorithm for computing the Discrete Fourier Transform (DFT) and its inverse, widely used in signal processing to analyze frequency components of a time-domain signal. 11

IP The Internet Protocol (IP) is a set of rules for addressing and routing packets across networks, ensuring data transmission between devices over the internet or local networks. 19

IPv4 Internet Protocol version 4 (IPv4) is the fourth version of IP, using a 32-bit address space to uniquely identify devices on a network, enabling communication over the internet. 19

KNN The K-Nearest Neighbors (KNN) algorithm is a supervised machine learning method used for classification and regression, which assigns a class to a data point based on the majority vote of its nearest neighbors in feature space. 6

LIS Locked-In Syndrome (LIS) is a neurological condition characterized by near-complete paralysis, preventing voluntary muscle movement except for limited eye movements. Patients remain cognitively intact but are unable to communicate without assistive technology.. 4

S/H Sample and Hold (S/H) is an electronic circuit technique used to capture and maintain a voltage level for a specific period, typically used in analog-to-digital conversion to stabilize rapidly changing signals. 19

SSVEP Steady-State Visual Evoked Potentials (SSVEPs) are periodic EEG responses elicited when a subject views a visual stimulus flickering at a constant frequency, commonly used in BCI applications for stimulus-based control. 1

STFT The Short-Time Fourier Transform (STFT) is a signal processing technique used to analyze the frequency content of a signal over time. By dividing the signal into short, overlapping segments and applying the Fourier Transform to each segment, the STFT provides a time-frequency representation of the signal, making it useful for analyzing non-stationary signals.. 17

UDP The User Datagram Protocol (UDP) is a connectionless communication protocol in the Internet Protocol (IP) suite that enables fast data transmission with minimal overhead, often used in real-time applications where low latency is prioritized over reliability. 10

VR Virtual Reality (VR) is an immersive technology that simulates a digital environment, allowing users to interact with and explore virtual worlds through specialized hardware such as head-mounted displays and motion controllers. 1

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