Acute Pain Detection Using Serious Games, Virtual Reality and Brain Computer Interfaces

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Abstract. Brain computer interface (BCI) technology can be used to measure pain. Brain activity is recorded and analyzed using BCI devices. Electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) are two technologies that allow researchers to evaluate and study pain. EEG monitors electrical activity in the brain and has been used to identify neural activity patterns linked with various kinds of pain, including acute and chronic pain. BCI technology can provide an objective and precise measure of pain, potentially leading to better pain management methods for people experiencing pain. More study in this field is required to find out how Virtual reality can be utilized in this field. However, further research is needed to validate the use of BCI technology as a reliable measure of pain in different populations and clinical settings. In this study, we review and study different methods of measuring pain using BCI. This technology enables researchers to observe and evaluate pain-related neural activity in real time. This could lead to the identification of neural patterns linked with pain, which could then be used to develop personalized therapy strategies for each patient. Furthermore, we could combine this technology with virtual reality to make a simulation that can monitor the patient's pain experience and assist with further therapy. This will provide a safe and controlled environment for patients to better understand their pain and learn the coping mechanisms by allowing patients to interact with and control the simulation using their brain activity. In addition, using virtual reality (VR) to create immersive training experiences for patients to enhance their mobility and agility. By designing training scenarios that mimic real-world tasks, such as playing music with a music box, petting a pet or gardening, we can help patients regain their confidence and independence while managing their pain in a controlled environment. Overall, the combination of brain computer interface and virtual reality technology has immense potential to revolutionize the way we treat chronic pain. This study aims to research and develop a serious game and simulation by combining two innovative technologies, VR, and BCI to understand patients' needs better and assist them with their chronic pain recovery and ease their pain. The game will provide patients with an immersive and interactive experience, allowing them to engage in activities that can help manage their pain, such as meditation, relaxation exercises, and cognitive-behavioral therapy.

Keywords: BCI, VR, Pain, Chronic Pain, EEG, Serious Games, Acute Pain

1 Introduction

EEG can be used to measure pain by recording electrical activity in the brain. When a person experiences pain, different parts of the brain become activated, which can be detected by measuring the electrical signals generated by the brain using electrodes placed on the scalp. The EEG signal is typically analyzed in the frequency domain, which involves breaking down the signal into different frequency components using mathematical techniques such as Fourier analysis. Different frequency components are associated with different types of brain activity, such as alpha, beta, delta, and theta waves. Research has shown that different patterns of EEG activity are associated with different types of pain, such as acute pain and chronic pain. For example, acute pain is associated with an increase in high-frequency beta waves, whereas chronic pain is associated with changes in the low-frequency alpha and theta waves. EEG can also be used to measure the effects of pain medications and other pain management strategies on brain activity, which can provide insights into how these treatments work, how they can be optimized and how effective the simulation and trainings are. Pain is a complex sensation affected by several factors. Therefore, the objective assessment of pain is a complex challenge. Research is being done into pain assessment and modern technologies and methodologies are driving the field forward. By employing modern Artificial Intelligence (AI), new paradigms and methodologies can be developed to accomplish objective pain assessment from brain activity.

Fourier analysis is a mathematical technique that is commonly used to analyze EEG signals in order to reduce the complexity in analyzing the data. This technique involves breaking down a complex signal into its component frequency parts, which can help identify patterns of neural activity associated with pain. To perform Fourier analysis on EEG signals, the signal is first divided into small segments, typically around one second in duration. These segments are then transformed from the time domain to the frequency domain using a Fourier transform algorithm. This produces a power spectrum, which shows the strength of each frequency component in the signal.

Peripheral is a VR Serious Game utilizing Brain-Computer Interfaces (BCIs) with potential for application in medicine and rehabilitation. It built upon the study titled: “A study of how virtual reality and brain computer interface can manipulate the brain” [1]. Peripheral is a tool for post-stroke motor function rehabilitation and the treatment of phantom limb pain. Combining Brain-Computer Interfaces and Virtual Reality technology with Serious Games offers a powerful and unique approach to medical treatment. Together these technologies are expected to provide highly immersive and engaging experiences. The goal is for the combination of SGs, VR, and BCIs to create a reinforcing loop, with each element amplifying the effectiveness of the others. Combining Brain-Computer Interfaces and Virtual Reality technology with Serious Games offers a powerful and unique approach to medical treatment. Peripheral features five levels with different tasks and settings. These levels have different challenges for the player. The development of these levels and the creation of their environments will be discussed in this article. Overall, this study provides a comprehensive examination of the technical and artistic aspects of developing Peripheral as a tool for post-stroke motor function rehabilitation and the treatment of phantom limb pain.

2 Background

2.1 Brain Computer Interfaces

A Brain Computer Interface is a system which can record brain activity and turn it into commands for computers to execute. BCIs can restore independence to disabled people by translating brain activities to control signals for computers and external devices [2]. Other uses for BCIs include epilepsy detection and intervention, car drowsiness detection and intervention and emotion tracking [3] .

Signal Acquisition. Brain activity can be recorded with several methods, such as EEG, Electrocorticography (ECoG), functional magnetic resonance imaging (fMRI) and positron emission tomography (PET). Recording methods are categorized as invasive and noninvasive. An invasive recording requires surgery, often inserting signal capturing devices placed to the brain's surface. However, invasive recording methods are associated with higher risk than their noninvasive counterparts due to surgery. Additionally, the signal from invasive devices degrades over time. Noninvasive recording methods ECoG is the most used compared to invasive recording method. Compared to different methods of signal acquisition, EEG is the most used method for recording brain activity [3].

Signal Processing. Once brain activity has been recorded as digital signals, the signals must be processed as the signal commonly contains noises. Noise includes signal artifacts such as eye blinks, heartbeats, and movement; environmental factors can also induce noise in the signals. This stage identifies the noise and extracts it from the signal, revealing the brain activity. These unwanted signal artifacts are removed through mathematical techniques, such as notching and filtering. Different recording methods yield different types of noise.

Feature Classification. This classification is needed in order to analyze the signal and distinguish features and artifacts which correspond to the user's intent. This is achieved through several methods, such as AI algorithms, statistical and visual analysis of the signals. Algorithms are calibrated on a set of signals with known intents. After calibration the algorithms can classify brain activity into intent.

Control. Once the brain activity has been translated into the user's intent, this stage turns the intent into a command for a computer to execute. This can involve controlling external devices, such as robots and communication tools. This stage usually includes providing feedback to the user based on their brain activity. By providing feedback the user is informed about the performance of the BCI and can more effectively change their brain activity to improve it.

Electroencephalography. EEG records electrical activity in the brain. This is done by placing electrodes on the scalp which measure the electrical potential in the brain. Intracranial EEG is also used, where electrodes are placed on or inside the brain. Due to the scalp and skull, scalp-based EEG results in a lower signal-to-noise ratio than intracranial methods. For scalp-based EEG, electrodes are placed according to the "10-20" system. **Error! Reference source not found.**illustrates the system with labels and placements for each electrode. The location and lateralization of the electrode determines each electrode's label [4]. Brain regions marked with different colors. The blue section represents the frontal lobe, yellow represents the parietal lobe, red represents the occipital lobe and the green sections represents temporal lobes. This system ensures consistency across disciplines using EEG.

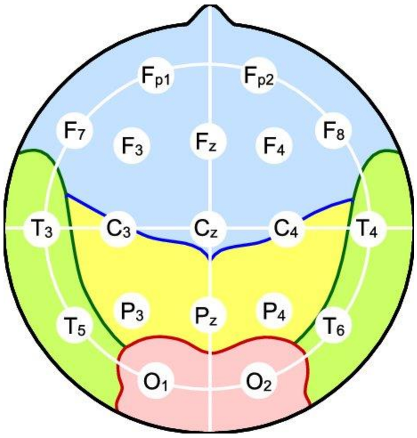

*Figure 1**: The "10-20" system** [4]*

Motor Imagery. Motor Imagery (MI) is a common BCI paradigm. MI is defined as imagining limb movements, but not executing the movement [5]. This involves the user's imagined movements being used as control signals for the computer. For example, a user may imagine moving their right hand and results of that would move a robotic arm. Sensorimotor rhythm (SMR) refers to the brain activity (rhythm) in the sensorimotor cortex. SMR is the most common technique of recording MI brain activity. SMR MI involves the imagination of large body parts and extremities. A common SMR paradigm is the imagination of hands, feet, and tongue movement. When imagining the movement of one of these body parts, changes in the SMR occur. These changes, Event Related Desynchronization (ERD) and Event Related Synchronization (ERS), are visible through analysis of the recorded EEG [5]. MI devices require calibration, often referred to as the calibration phase, usually involving recording many sessions of imagination for several body parts. Individuals have different brain activity and patterns; therefore, calibration should be done individually. This calibration is a drawback and affects the usability of the BCI because it is a time-consuming process [5]. Through SMR or other paradigms, BCIs can differentiate between imagined body parts and this classification is used as the control signal. Once a MI system is calibrated, the BCI records EEG and classifies in real-time, enabling real-time control. For future widespread adoption of this paradigm several issues remain to be solved, such as the calibration phase [5].

2.2 Serious Games

One of the addressed issues with conventional rehabilitation is that therapy sessions might be tedious due to the repetition of activities, and simplicity of the tasks. Gamifying the tasks can motivate, engage, and foster adherence to treatment in patients. [6] Therapists can also benefit from automated and customizable sessions for individual patients. Francesco discussed in their article that serious games biggest strength is their effectiveness in increasing motivation and engagement. Game's ability to provide real-time feedback about performance is a crucial factor [7]. Therefore, our focus in this study is to design and develop a serious game that is customizable and engaging enough to keep patients interested in doing the therapy session. This will allow patients will less mobility to have a system that they can work with at home or any places they prefer to.

2.3 Fourier Analysis

Acute pain is often associated with an increase in high-frequency beta waves, whereas chronic pain is associated with changes in the low-frequency alpha and theta waves. By analyzing the power spectrum of the EEG signal, researchers can identify these patterns of neural activity and use them to measure pain. The mathematical formula used for Fourier analysis is called the Fourier transform (FT). There are different types of Fourier transforms, such as the Discrete Fourier transform (DFT) and the Fast Fourier transform (FFT), but they all use similar principles. The Fourier transform converts a signal from the time domain to the frequency domain, by decomposing the signal into a sum of sine and cosine waves with different frequencies. Formula 1 presents the Fourier transform.

$$\hat{f}(\xi) = \int_{-\infty}^{\infty} f(x)\, e^{-i2\pi\xi x}\, dx. \tag{1}$$

Where F(w) is the frequency domain representation of the signal, f(t) is the time domain signal, (w) is the angular frequency (in radians per second), and (i) is the imaginary unit. The inverse Fourier transform is used to convert a signal from the frequency domain back to the time domain, and its formula is:

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}_3(\omega)\, e^{i\omega x}\, d\omega. \tag{2}$$

Where f(x) is the time domain signal, F(w) is the frequency domain representation of the signal, and $\frac{1}{2\pi}$ is a normalization factor. In practice, these formulas are implemented using numerical algorithms, such as the FFT, which allows for efficient computation of the Fourier transform. For signal processing and analysis, the time-frequency domain is often needed. The Fourier transform only yields the frequency domain and all information about time is lost. The same applies for the signal in the time domain where no frequency information is available. The Short-Time Fourier transform translates the time domain into the time-frequency domain, and is defined as:

$$X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-i\omega t}\,dt \tag{3}$$

Where x(t) is the time-domain signal. w(t) is a window function. In practice this applies a Fourier transformation to a windowed segment of the time domain signal and results in frequency information at specific time periods of the signal [8].

2.4 Pain

Pain is a complex and subjective experience that is an integral part of the human body's Central Nervous System (CNS) [9]. It is a crucial mechanism that notifies the body to potential harm and further damage. Pain is a multi-dimensional experience that involves both sensory and emotional components. Pain management is pivotal for many patient groups across the world. The consequences of unrelieved pain are associated with increased risk of chronic pain and reduced quality of life for patients [10, 11]. Most pain assessments are conducted using self-reported Visual Analog Scales (VAS) and questionaries. However, these methods lack objectivity. Additionally, it is not suitable for many patient groups, for example nonverbal and cognitively impaired patients. Pain management is primarily done using opioids [11]. This poses several issues, such as side effects and addiction. And therefore, opioids are not suitable for every patient, however multimodal analgesia is appropriate for everyone [10]. Objective pain assessment is an important factor in administering appropriate analgesia for patients. This raises the need for objective pain assessment methodologies and technologies.

3 Methodology

3.1 Motor Imagery Method

A custom MI system was developed for Peripheral. This system uses custom Python scripts for networking and labeling, together with NeuroPype Academic for ML classification. The output of NeuroPype is collected by custom Python scripts and sent to Peripheral which enables MI as control signals for Peripheral. The process involves labeling EEG data with the user's intent, for example labeling right hand movement as "Right". The calibration is conducted by trials, each trial lasts 4 seconds and labels one intention. The MI calibration starts with warmup trials. Once the system has been calibrated, the user can use MI for real-time control. A typical calibration phase can include 30 trials for classes "Left" and "Right" with 1 second pause between each trial and 30 second pause after every 30 trials. Fig.2 shows the visual interface shown to the user during MI calibration during a warmup trail for "Left" calibration. The calibration visuals are created using custom Python scripts. The blue box shown moves in the direction of class being labeled. The trial is over once the box reaches the edge of the screen, then text appears informing about the what the next class to be trained is.

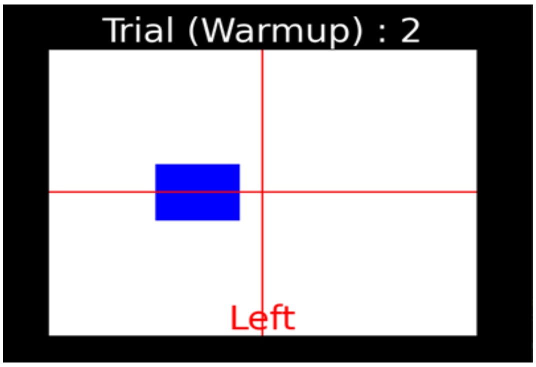

Fig. 2. Visual interface for MI calibration

3.2 Peripheral

Peripheral was developed using Unreal Engine 5. Peripheral can be played with VR, BCI and both at the same time. Peripheral supports Emotiv Insigth, Emotiv Epoc and OpenBCI Cytyon+Daisy for BCI systems. **Fig.3** shows Peripheral being played with BCI control. The hand shown in the figure is the players interface to interact with the game world. The hand is controlled by MI as described in the previous section. It can interact with and grab objects in the game world. The hand and BCI control can be deactivated at any time during gameplay. Once deactivated the hand will disappear from the screen and no longer be affected by the MI. All the tasks in the levels of Peripheral are designed for this control method.

Fig. 3. Screenshot of Peripheral with BCI control

3.3 Pain Detection

The objective of pain detection is to objectively assess pain from EEG signals. This is implemented through AI, specifically a Deep Learning (DL) algorithm. DL algorithms can make predictions and classifications by identifying patterns in data. Typically, DL algorithms require large datasets for effective training and classification. However, for this article, access to substantial data containing scalp EEG recordings during acute pain sensation was unavailable. To address this limitation, a novel dataset was created by introducing pain-correlated signal artifacts into EEG recordings where no actual pain was experienced. Pain artifacts were defined from studying articles : [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26] and [27]. A pain artifact is defined as:

$$A = \{b, c, e, d, t\} (4)$$

where (b) represents the affected band ranges. (c) represents the channels affected. (e) signifies the effect. (d) represents the delay. (t) represents the duration. The EEG recordings were obtained from one of the authors during daily activity. The EEG data was sampled into smaller sections. For half of the samples, a pain artifact, timing, and intensity level ranging from 1 to 10 were randomly selected. The remaining samples are not imposed with pain. The chosen artifact, timing and intensity are saved as labels for the AI algorithm.

The set of all the samples are defined as:

$$S_n = \{S_1, S_2, \dots, S_N\} \ (5)$$

where N is the total amount of samples.

The label for each sample is defined as:

$$L = \{(A_1, T_1, I_1), (A_2, T_2, T_3), \dots, (A_N, T_N, I_N)\} \ (6)$$

where L is the set of all samples with imposed pain artifacts and N is the total amount of samples. Each label contains the artifact, timing, and intensity.

The signal is imposed with the pain artifact by attenuating frequencies by the intensity at specific times, and its formula is:

$$K_n = \ STFT(S_n[A_c]])[A_b] + \ A_e * I_n * rect(\mathrm{t},\ T + A_d,\ T + A_d + A_t) (7)$$

where S_n is the original EEG sample. A_c returns the channels defined by the artifact. STFT() is the Short-Time Fourier transform function resulting in a time-frequency domain signal. From the time-frequency domain, the frequency amplitudes over the whole time dimension at A_b frequencies are selected. t represents the time. The frequencies are attenuated by the effect A_e multiplied by the intensity I. This attenuation is only applied while the rectangular function returns 1, the rectangular function is defined as:

$$rect(t,a,b) = \begin{cases} 1, & if\ a \leq t \leq b \\ 0, & otherwise \end{cases} \quad (8)$$

The reconstructed signal is defined as:

$$F_n = ISTFT(K_n) \ (9)$$

Where ISTFT () is the Inverse Short-Time Fourier transformation function and S_n is the reconstructed signal in the time domain. The signal is reconstrued to the time domain via the Inverse Short-Time Fourier transform. The samples imposed with pain artifacts and their corresponding labels are saved to file.

Fig. 4. illustrates how a pain artifact affects the signal. The left signal shows the EEG recording at a single electrode. The right signal shows the reconstructed signal after a pain artifact has been imposed on it using the methodology explained in this section. At the 3 seconds mark, certain frequencies exhibit an increase, resulting in an overall enchantment in signal strength.

Fig. 5. provides spectrograms before and after the introduction of a pain artifact. The modified spectrogram demonstrates heightened activity in the 5 Hz to 30 Hz range, lasting for 1 second, beginning at the 3 second mark.

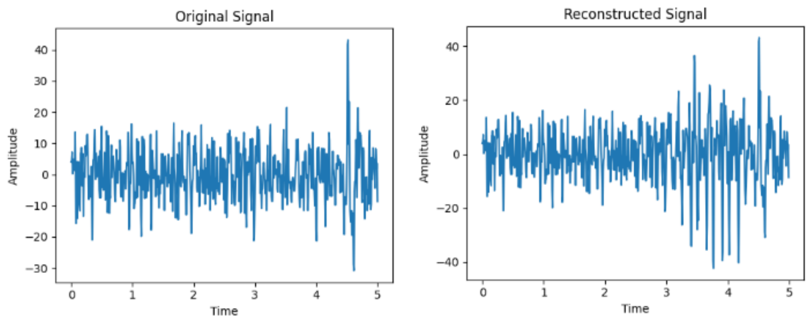

Fig. 4. Example of an EEG signal imposed with a pain artifact.

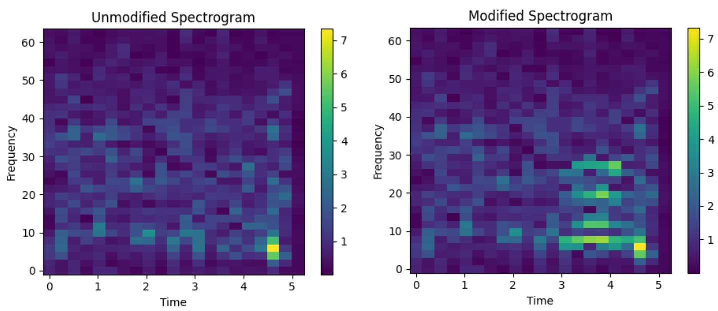

Fig. 5. Example of a spectrogram imposed with a pain artifact.

The system for imposing pain artifacts on EEG signal is implemented with custom Python scripts and custom files. Changes to the methodology can be easily implemented via simple changes in files and scripts. A Convolutional Neural Network (CNN) algorithm is used for classification and is implemented by custom Python scripts. The EEG samples were recorded with 16 channels at 125 Hz and sampled to 5 second samples. This results in each sample being 16 channels with 625 measures of electrical activity. The CNN is fed the EEG data with labels as defined in the previous sections. By training the CNN on data with the correct labels, it will learn to recognize the artifacts imposed on the signals. Once this is achieved, it should be able to recognize real pain sensation from EEG data.

4 Prototype and design

4.1 VR and BCI

In this study, we tried different way to combine VR and BCI data acquisition and synchronize feedbacks and data. There are some limitations due to lack of technology at the time of this research that does not allow us to use both technologies at the same time. There are however companies like OpenBCI that are working on a device called Galea that will suit this purpose; however, the headset is still not available in market. To overcome this issue and limitations, a modified version of the OpenBCI UltraCortex Mark IV was designed that can be used at the same time as a Meta Quest 2 VR headset.

4.2 Peripheral's Lobby

The lobby is the first level of Peripheral. It serves as an introduction to the game mechanics and does not contain any tasks or challenge for the player. The lobby allows the player to get familiar with the controls, such as moving the hand with BCI, without attempting to complete the challenges at the same time. Allowing the player to familiarize themselves to the game mechanics can increase their performance and reduce the frustration during entering the actual levels. While the lobby can be a tutorial space, it can be used as a safe space to come back to and relax, due to the calm music and peaceful atmosphere as shown in **Fig.6.**

Fig. 6. The lobby

4.3 Levels

Level 1: Wood Stacking. This level places the player in front a shed and surrounded by wood logs. The objective is for the player to grab the logs and stack them in the shed. Moving the wood logs only requires left and right movement. This results in this level being the easiest of all the levels, only requiring one movement axis. This being the first level can reduce the likelihood of people being alienated by the difficulty of BCI control. A flow is created when the game increases in difficulty over time. This is when the game is not too hard and not too easy, and when the player will enjoy the game most [28]. **Fig.7** shows an overview of the level design. Once the level starts the player is placed slightly behind the two standing wood logs. This level design is inspired by Norwegian wood stacking cultural practice and tradition in Norway which reflects the country's relationship with nature, usefulness, and appreciation for craftsmanship.

Fig. 7. The wood stacking level.

Level 2: Music Box. This level implements the elements of music and sound to engage the player and evoke a sense of nostalgia. As shown in **Fig.8** the player is presented with a music box that is interactable. Attached to it is a handle that can be spun. Once the handle has been spun the music box starts playing music and the ballerina starts to dance. Spinning the handle requires circular hand movement (up, down, forward, and backward). This level increases the difficulty by requiring movement on more axis than the previous level. The goal of this level is to increase player engagement by giving them musical and visual feedback from their successful turning of the handle.

Fig. 8. The music box level design

Level 3: Animal Petting. In this level, the player is provided with a virtual dog, as shown in Fig.9 The level is set in a wide grassy field. The dog responds to the player's actions with animations: Petting its head results in it sitting down and wagging its tail, petting its belly results in it doing a backflip, and petting its backside results in it barking at the player. Additionally, the player can play fetch with the dog. Throwing an object causes the dog to run after it, catch it and return it to the player. The goal for this level is to engage the player by providing them with feedback for playing with the dog. Study shows that animal contact can improve mood in children and adults with physical or mental health problems [29].

Fig. 9. The animal level design

Level 4: Painting. On top a cliff, facing the ocean, the player is provided with a blank canvas. The player can freely paint on the canvas and select different colors. The objective of this level is to engage the player and spark their creativity and express themselves through art. Fig.10 shows the canvas with exemplary painting on it and the available colors to the right of it.

Fig. 10. The painting level Design

5 Results and Discussion

5.1 Clinical applications for Peripheral

During a stroke, the blood supply can be cut off to parts of the brain, potentially resulting in damage when cells lose blood and oxygen-flow [30]. Many stroke survivors suffer loss of motor functions due to brain damage in the regions that control motor functions. Loss in motor function can be disabling and reduce independence [31]. Reduction in independence is associated with post-stroke depression and reduced quality of life [32]. Motor imagery-based rehabilitation for post-stroke motor function loss has shown great potential and successful clinical application [33] [34]. These treatments involve the patient consciously imagining motor function of the limb with lost motor function. The act of imagination activates the same brain areas which are associated with the actual movement of the limb. Post-stroke motor function rehabilitation relies on neuroplasticity. Neuroplasticity is the central nervous system's ability to reorganize and restructure itself. Adaptive neuroplasticity occurs after long term or continuous stimuli [35]. The goal is to induce neuroplasticity by controlling Peripheral and being able to complete tasks with the imagination of the limb with lost motor function. Over several play sessions, long-term stimuli of the damaged brain area can be achieved, potentially invoking neuroplasticity. If neuroplasticity does occur, the patient will gradually regain motor functionality.

EEG can measure brain activity directly above damaged parts of the sensorimotor cortex. Compared to other methods, such as mirror therapy, EEG-based motor imagery rehabilitations can give the patient direct feedback based on the activation of the area. The movement of the controlled hand in Peripheral is real-time feedback to the player, allowing them to see how well they recruit the brain areas and can adjust accordingly. Up to 80% of amputees suffer from phantom limb pain (PLP) after amputation [36] [37]. Phantom limb pain is a result from maladaptive neuroplasticity. However, this indicates neuroplasticity can relieve and stop phantom pains. By controlling Peripheral and completing the levels, adaptive neuroplasticity can be induced. Peripheral Objective pain assessment from EEG combined with MI training using Peripheral can grant insight into the brain activity that determines phantom limb.

5.2 Improving Peripheral

The calibration of MI for Peripheral is conducted with external programs. The technical expertise needed to operate the MI calibration may the decrease accessibility of Peripheral. As shown in Fig.3, the MI calibration does not provide feedback to the user. Providing feedback in this stage can greatly improve the calibration results. By incorporating the MI calibration phase into Peripheral a more seamless experience can be achieved and more feedback can be given to the user. Peripheral only supports Meta Oculus VR headsets. Including support for more VR headsets can increase the accessibility of the game. By including pain detection into Peripheral, treatments can be customized and adjusted according to pain levels. Pain thresholds can be set, and the gameplay can be stopped when it's reached. The pain assessment can be visualized on the screen and limits can be adjusted based on feedback from it. The data and visualization would allow the patient to see the improvement and effectiveness of the rehabilitation throughout the process. Objective assessment of pain can open many doors for researchers and doctors.

5.3 Results from Pain Detection CNN

The CNN was trained on 1000, 5000 and 10000 samples of EEG signals with varying pain artifacts, at varying times and intensities, the objective being for the algorithm to be able to detect if pain occurred during the EEG signal. EEG recordings where pain occurred were obtained by one of the authors of this article. Pain was induced by the author submerging a hand in cold water. However, no correlation between real pain sensation and the output of the CNN algorithm was observed.

6 Further Research

Chronic pain is more prevalent in comparison to acute pain, where acute pain may only need short term analgesia, but chronic pain patients can require long term analgesia. Due to side effects and addiction risks, long analgesia can prove a substantial issue for chronic pain patients. Examining the brain activity of chronic pain patents with EEG has potential to give valuable insights into the mechanisms of chronic pain and help to relieve the pain. Research has demonstrated that chronic pain is linked to increased alpha and theta brain activity [38]. By being able to objectively detect the presence of chronic pain through EEG analysis, healthcare professionals can attain a deeper understanding of the condition and improve patient outcomes.

The CNN algorithm. The algorithm for pain detection yielded unsuccessful classification of real pain signals. The CNN algorithm was trained on thousands of samples and could accurately classify the imposed pain from the EEG signals without imposed pain, but this did not translate to classification of real pain signals. Several factors may contribute to this. The chosen pain artifacts, for example reduction in alpha waves over the frontal cortex, may not correlate with acute pain and therefore calibrate the CNN with wrong information. The real EEG data may not have been recorded with high enough resolution. Only 16 channels were recorded, a relatively small number compared to medical EEG equipment. The pain detection method can be improved in several ways for increasing the likelihood of success. For this study, only time-domain signals were analyzed by the CNN algorithm. More insight can be gained by including frequency and time-frequency domain signals into the analysis. The EEG was recorded with a lack of electrodes placed at the central regions of the scalp. This results in electrodes FCz and Cz not being included in the EEG recordings. Both of these electrodes have potential for pain detection [39]. With higher resolution EEG with more electrodes, these electrodes could be included and more detailed could be extracted from the brain activity. For optimal detail coverage of the whole “10-20” system is needed. The EEG data with real pain sensations was recorded 20 times, each for 5 seconds. This limits the testing of the algorithm to these 20 trials which may be inadequate. To test the pain detection better, more EEG recordings with real pain sensations are needed. The systems developed for this method will be further developed and employed to closer achieve the goal of pain assessment.

By implementing a virtual avatar for the player into Peripheral, more treatment paradigms and higher embodiment can be achieved. A virtual avatar for VR gameplay is intended to map to the player’s body, an estimation can be made through inverse kinematics based on the VR headset position. For both motor function rehabilitation and phantom limb pain rehabilitation, this method could increase embodiment, engagement and therefore increase neuroplasticity. The avatar's hand can be mapped to a motion controller held by the player, contralateral to the amputation or disabled limb. The avatar's other arm could be controlled by MI, providing another dimension of feedback to the player. If good control using this method can be achieved, several other paradigms can be employed for rehabilitation or controlling external devices.

7 Conclusion

Peripheral is a serious game combined with VR and BCI technologies. Elements from SGs, VR, and BCIs have been combined with the objective to create a reinforcing loop, with each element amplifying the effectiveness of the others. How Peripheral can be used for post-stroke motor function rehabilitation and phantom limb pain rehabilitation have been discussed. Each level of Peripheral contains tasks for the player to complete. By developing tasks requiring motor functionality, interventions can be developed, and the performance of the patient can be objectively assessed. Overall, multidisciplinary approaches can improve patient outcomes and the authors implore researchers to conduct further study of this approach. Research was conducted to define signal artifacts that correlate with subjective pain sensations. EEG data where no pain sensation occurred was imposed with these artifacts to create a novel dataset. A CNN algorithm was trained on EEG data imposed with signal artifacts and tested with EEG data where real pain occurred. The objective was to objectively assess pain by analyzing brain activity. Despite of not resulting in successful classification of pain, this method can be further improved in pursuit of objective pain assessment using noninvasive EEG. Level designs have been tested and improved to help patients mentally and physically. More levels will be designed throughout of the completion of this project.

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