Developing a Serious Game for Acute Pain Detection by Utilizing Virtual Reality and Brain-Computer Interfaces

Meisam Taheri [1] [0000-0001-5896-3449], Adam Emile Aske [1], Kevin Tan[1]

[1] Inland Norway University, Hamar, Norway
meisam.taheri@inn.no

Abstract. Brain computer interface (BCI) technology can be used to measure pain. Brain activity is recorded and analyzed using BCI devices. The use of Brain-Computer Interface (BCI) technology for pain measurement is an area of ongoing research and development. While there is no single definitive proof at this time, there is a growing body of evidence and research that supports the idea that BCI technology can provide objective and precise measurements of the pain. BCI enables researchers to observe and evaluate pain-related neural activity 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 VR 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 by allowing patients to interact simulation elements using their brain activity and get real-time feedback. Overall, the combination of brain computer interface and virtual reality technology has immense potential to revolutionize the way we detect and ease pain. The aim is to develop a simulation that provides patients with an immersive and interactive environment, allowing them to engage in activities that can help manage their pain, such as meditation, relaxation exercises, and cognitive-behavioral therapy. In this study, authors worked on a method to show how pain can be detected and visualized and used in the simulation.

Keywords: BCI, VR, Pain, Acute Pain, Game, Simulation

1 Introduction

Brain-Computer Interface (BCI) represents a technology with considerable promise, particularly in its capacity to assist individuals confronting physiological and physical challenges [1]. Additionally, BCI has the potential to serve as a means for pain measurement through the recording of electrical brain activity. When a person experiences pain, various 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 distinct 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 [2]. 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 commonly used to analyze EEG signals 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.

Background

1.1 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 [3]. Other uses for BCIs include epilepsy detection and intervention, car drowsiness detection and intervention and emotion tracking [4] .

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 [4].

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 to analyze the signal and distinguish features and artifacts corresponding 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 where the location and lateralization of the electrode determines each electrode's label [5]. 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 section represents temporal lobes. This system ensures consistency across disciplines using EEG.

1.2 Serious Games

One of the issues addressed with conventional rehabilitation is that therapy sessions might be being 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. A 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 place they prefer to.

1.3 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 [8].

1.4 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 of 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 a key factor in administering appropriate analgesia for patients. This raises the need for objective pain assessment methodologies and technologies.

2 Methodology

2.1 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:

$$A = \{b, c, e, d, t\} (1)$$

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:

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

where N is the total amount of samples.

The label for each sample is defined as:

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

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:

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

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:

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

The reconstructed signal is defined as:

$$F_n = ISTFT(K_n) \text{ (9)}$$

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.

Figure 1 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.

Figure 2 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.

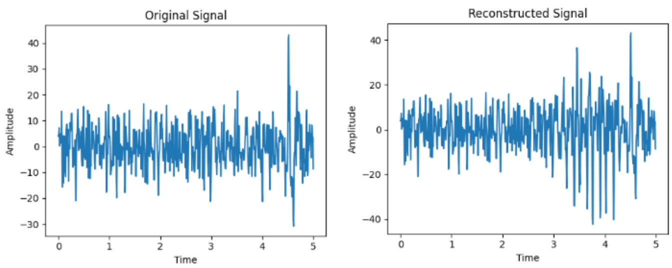

Figure 1 Example of a time-series imposed with a pain artifact.

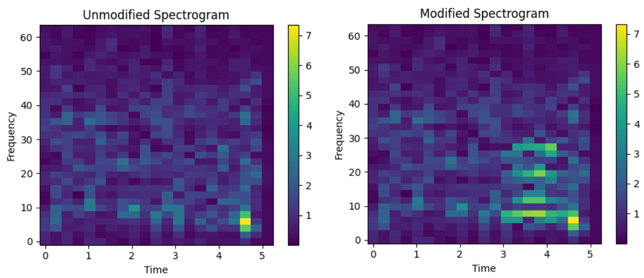

Figure 2 Example of a spectrogram imposed with a pain artifact.

The method described for imposing pain artifacts on EEG signal was implemented with custom Python scripts and files. To get real EEG data, EEG was recorded by the authors for 2 hours during regular daily activity while wearing an EEG recording device. Electrodes FP1, FP2, AF3, AF4, F3, F4, F7, F8, FC5, FC6, T3, T4, T5, T6, P3 and P4 were used and recorded at 125 Hz. The 2 hours of EEG data were split into 5 second segments and saved in files accessible to the Python scripts. To generate a sample with imposed pain artifact, a Python script loads a sample from the real EEG data. Then it chooses a pain artifact to impose and uses the algorithm explained earlier to impose pain artifacts on it.

A Convolutional Neural Network (CNN) model is used for classification and is implemented with the TensorFlow API in custom Python scripts. The CNN model is comprised of layers and starts with an input layer. The EEG samples were recorded with 16 channels at 125 Hz for 5 seconds. Thus, the shape of the input layer is 16 by 625. Following the input layer, 3 convolutional layers, each followed by an activation layer and a pooling layer. Following the third convolution, a flattened layer and a fully connected layer completes the CNN model. The model is compiled with a binary-crossentropy loss function and Adam-optimizer. The CNN model train to classify each sample into either no-pain or pain, hence a binary loss function. The goal being that the CNN could learn to classify real pain from no-pain because it has trained to classify fake pain from no-pain.

3 Results and Discussion

3.1 Results from Pain Detection CNN

EEG samples with real pain sensations were obtained by one of the authors of this article. EEG was recorded in 5 seconds samples and pain was induced by the author submerging a hand in icy water. This was done 20 times. 3 CNN models were trained on EEG samples, respectively 500, 1000 and 10000 sample sizes. Half the samples contained generated pain artifacts and the rest were regular EEG samples without pain. Every model was able to distinguish between no pain and pain with higher than 95% accuracy. All the models were fed the EEG samples with real pain. However, no correlation between real pain sensation and the output of the CNN algorithm was observed. This means that the CNN model did not find correlation between the imposed pain artifacts to real pain artifacts in EEG signals. Further improvements can be made with a CNN model created for EEG data.

4 Further Research

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 incorrect 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 electrodes have potential for pain detection [28]. With higher resolution EEG and more electrodes more information could be extracted from the brain activity. The EEG data with real pain sensations was recorded 20 times, each for 5 seconds. More EEG recordings with real pain sensations are needed to improve testability of the CNN model.

5 Conclusion

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 not resulting in successful classification of pain, this method can be further improved in pursuit of objective pain assessment using noninvasive EEG.

6 References

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