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Using Machine Learning Techniques to Model Encoder/Decoder Pair for Non-invasive Electroencephalographic Wireless Signal Transmission

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By

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Dedication

I wish to dedicate this thesis to the following:

- My mother, Marie Michelle, you are the source of my perseverance and dedication.
- My father, Ernst Murat, you are the source of my strength and attention to detail.
- My girls, Isabelle and Annalisse, you are the force that makes me strive for a better tomorrow. I miss you both.
- My love, Israa, thank you for showing me a dream come true.
- My best friend, Imad, I would not be here if it was not for you.
- Major Westley Hinckley, thank you for being my friend. I hope you find peace in the afterlife.
- My very first mentor, Wayne Thomas, without you, I would never know true work ethic.

Thank you. You all touched my life and helped me forge the man I am today.

Acknowledgments

I am eternally grateful to the four professors who guided my educational career. Dr. Adriane Randolph, thank you for seeing the whole of me. This is a concept I intend to employ in my journey. Thank you for the push when I needed it and for showing me how to make my fantasy into reality. Dr. Summit Chakravarty, working with you has been a joy, and your insight is greatly appreciated. I can safely say that without you, this paper would not exist. Dr. Kun Suo was the very first professor I worked for. You open my eyes to this world I am now striving to join. Thank you for trusting me. Dr. Jose Garrido, thank you for being patient with me and entertaining my crazy ideas. Without you, Dr. G., this committee would not exist, and I would have never considered the thesis path. To all, you are the spark that ignites the passion and curiosity that drive the world of academia and research.

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Abstract

This study investigated the application and enhancement of Non-Invasive Brain-Computer Interfaces (NI-BCIs), focused on enhancing the efficiency and effectiveness of this technology for individuals with severe physical limitations. The core research goal was to improve current limitations associated with wires, noise, and invasive procedures often associated with BCI technology. The key discussed solution involves developing an optimized Encoder/Decoder (E/D) pair using machine learning techniques, particularly those borrowed from Generative Adversarial Networks (GAN) and other Deep Neural Networks, to minimize data transmission and ensure robustness against data degradation. The study highlighted the crucial role of machine learning in self-adjusting and isolating essential data for accurate and efficient classification. The research design involved training this E/D pair to unlock applications of NI EEG BCIs, such as speech synthesis and seamless control of mobile devices. This research successfully trained the E/D pair with a compression ratio of 500 to 75 data points. With parallel processing, this paper successfully processed and transmitted 36 channels of EEG data without data loss at 97% accuracy in 0.0752s. By successfully developing a robust E/D pair, the study aims to revolutionize BCI technology, paving the way for more intuitive interfaces and significantly improving the quality of life for locked-in individuals. This research thus contributes to advancements in NI-BCIs, harnessing machine learning to address current limitations and unlock new possibilities for this critical technology.

Introduction

As technology is evolving, so does the way we interface with it. Interface developers tried to remove discomfort throughout the years and connect devices to users intuitively. A system connected to the brain would remove many barriers to an intuitive system, hence the wide range of brain-computer interface (BCI) research. Brain-computer interface research has facilitated paralyzed people to move independently, use a computer, and send emails [1]. Unfortunately, because of the current limitations and invasiveness of the technology, BCIs were often more viable in highly regulated medical studies or as a novelty [2]. BCIs could be so much more. This study focused on the Non-Invasive (NI) BCIs, which refer to technology that does not require surgery.

Non-Invasive Brain-Computer Interfaces (NI-BCI) are electroencephalographic- (EEG) based devices. EEGs use electrodes to detect the electromagnetic pulse emitted by neurons as they are firing. A system then processes and interprets the user's intent from the signals from the electrodes [3]. The system uses the classified intents and launches the appropriate sub-routines. These sub-routines manifest as an action on a platform or the physical world [3]. BCIs can enhance how we interact with our environment by making the interface more intuitive. With the proper research, NI BCIs will make elevating the quality of life of minimal patients more available [2].

Based on previous experience and the literature review, some of the most significant limitations of BCI technology are related to wires and noise [3]. The EEG electrodes pick up electrical signals, which means they detect all electrical signals. They also register muscle contractions, eye movements, and involuntary movements like swallowing or blinking. These noises affect our ability to classify intent, especially motor imagery (MI) applications [3]; they make classification slow and inaccurate. The previous can increase the user's frustration and reduce concentration [2]. Besides using machine learning (ML) to aid in the classification, the next best thing is to use invasive BCIs, comparable to the one Neuralink is developing [4]. Because of the invasive nature, the previous must undergo rigorous testing and get approval from the Food and Drug Administration (FDA) before human trials. Those FDA approvals can take time to ensure safety and effectiveness.

The encoder/decoder (E/D) algorithms must minimize the number of bytes to compromise the transmission speed to eliminate the wires. The previous must also be robust enough to account for data degradation. *Is it possible to use ML to develop such an E/D pair?* Further, *can ML model and optimize an E/D pair that can transmit over Bluetooth without compromising speed and classification?* This study tried to answer these questions.

This research borrowed techniques from Long Short-Term Memory (LSTM) and other Deep Neural Networks. This research especially focused on the backpropagation of these machine learning techniques. This experiment modified these techniques to fit our goals. These ML techniques were not one size fits all and were at the core of the success of this project.

Suppose we maintained or increased the speed of transmission and classification accuracy. In that case, we would unlock specific NI EEG BCIs applications, significantly improving locked-in patients' quality of life [2]. For example, an NI EEG device could be used for speech synthesis or to control a mobile phone for more efficient communication.

I trained an E/D pair. Machine learning techniques self-adjusted and isolated the crucial bites to classification. This triage only codified and transmitted what was needed. I outlined in the research design subsection of the methodology how I tested the E/D pair.

In the following sections, I present the literature review that led to the inception of this study. Then I present the methodologies, including a research design and a dataset overview. Afterward, I discuss the potential implication of the research by speculating on the future of BCI technology.

Literature Review

In Fanfan et al. [2], the study proposed using an NI BCI in an information system as a communication aid. This study focused on a specific medical application. They researched how to improve the quality of life of locked-in patients. Also, their proposed system can aid in the decision-making process of caregivers.

In [3] and [5], the role of BCIs in control and communication was discussed. The features of BCI and its crucial parts were discussed. Furthermore, the different sorts of BCI based on the utilization of electrophysical signals were described, and the critical problems in BCI-based control and communication systems were highlighted.

[3] focused on feature extraction using machine learning techniques. MI-EEG is a self-controlled EEG that does not involve any external stimulus. In the MI-oriented BCI mechanism, the subject is urged to visualize moving distinct body parts to trigger neuronal activities in particular brain regions linked with the movements.

In [1], Their team explained the role of BCIs in communication and motor rehabilitation. This study discussed BCIs for communication in individuals with locked-in disorders or paralysis. They also described BCI use in motor rehabilitation after spinal cord impairment and severe stroke. This study reported the promising advantages of BCIs in clinical applications.

In [6], The authors discussed the different presentation methods for EEG-based communication. They compared them to determine a means to increase the communication speed. They compared word-based, letter-based, and icon-based augmentative and alternative communication (AAC), event-related potential (ERP), and rapid serial visual presentation (RSVP). They also experimented with combinations of the previously listed techniques.

In [7], the author presented a review of all of the research involving the application of ML in BCI. The author covered topics ranging from ERP, RSVP, AAC, mental state, MI, and EEG, to selection classification. This paper compared all the results obtained using Support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), linear regression, and many more.

In [8], the ML approach was proposed for real-time EEG signal analysis. It even discussed the significance of ML schemes for mental condition monitoring and EEG-oriented BCI applications. The previous has the potential to assist as a diagnostic tool.

In [9], the researchers investigated several classification schemes for EEG-BCI systems. Additionally, they identified numerous challenges for further strengthening the EEG categorization performance in BCI.

In [10], They reviewed different classification approaches for EEG-oriented BCIs. This study reviewed five classification approaches: nearest neighbor schemes, non-linear Bayesian schemes, neural networks, linear classifiers, and fusions of classifiers. This study revealed that among five categories, fusions of classifiers seemed very practical for contemporaneous BCI experiments.

Unfortunately, there is very little literature available on EEG radio transmission. This project is at the forefront of exploring better algorithms and hardware for EEG signal transmission. This researcher intends to explore this subject thoroughly. The above led us to develop the theory expressed in the introduction section. Training the encoder/decoder pair using machine learning techniques will increase transmission speed and maintain data integrity. The model will isolate crucial information and encode what is needed for classification. The previous will minimize the number of bytes transmitted. Also, when the algorithm introduces noise, the decoder will recover the data, and the classifier should maintain its performance.

Methodology

Research Design

Using machine learning techniques, I developed an encoder/decoder (E/D) pair. The encoder will compress the multichannel EEG signals to be transmitted wirelessly, and the decoder will, in turn, decompress the data. Eventually, the classifier will label the signal, and errors will quantify the E/D pair's performance (Figure 1).

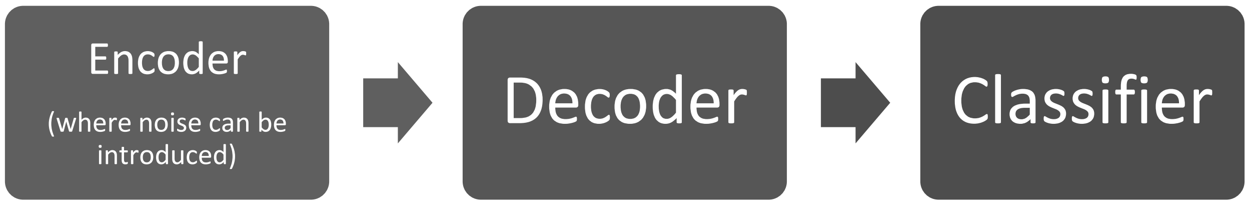

Figure 1 Algorithm Structure

We will use the dataset to train the classifier. Then the classifier will label the testing portion of the dataset to get control. The same test portion will pass through the encoder, once without noise and once with noise. The first pass will serve to determine if the whole algorithm works. The second pass will determine if our encoder/decoder pair works under simulated wireless conditions. The noise will be present at the encoder, and we will adjust its level to test the limits of the E/D pair. After the classifier labels each batch, we will compare the results. The above is an experiment group. We must use the same testing dataset for each experiment group to understand the performance of the E/D pair better (Figure 2). Then, the experiment operator will make the necessary adjustments and repeat the above steps to maximize the accuracy of the classifier with new testing datasets.

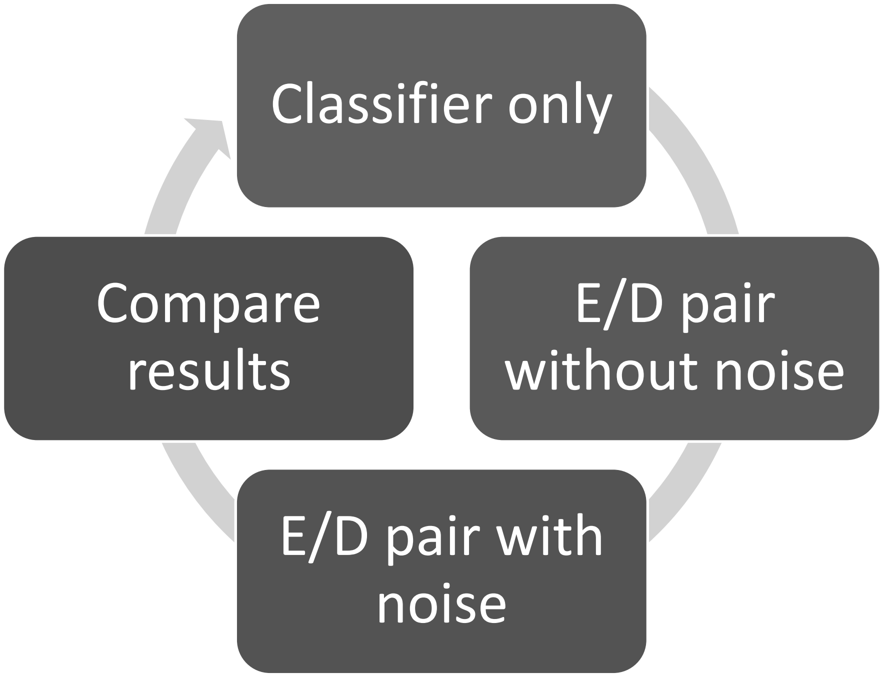

Figure 2 Experiment Group

The code will split the dataset according to the standard 70% training and 30% testing ratio. Furthermore, the algorithm will organize the data into 500 data points frames per channel. Each frame will go through each transformative step and require an input size of 500x16. We chose 500 hundred because it worked best during the single-channel proof of concept performed before this proposal.

Proof of Concept

We initiated a proof of concept as part of a larger team effort. Investigation into various ML and deep learning techniques yielded a first test in partnership with an undergraduate researcher. The objective of the proof was to verify if this proposal is possible, specifically examining: Can we model an encoder/decoder pair to remove as much unnecessary data as possible while being robust enough to maintain data integrity in a wireless transmission environment?

Autoencoders are neural networks that take input vectors, compress them in a hidden layer, and expand them back to their original size as accurately as possible [11]. The idea is to process the input vectors into a smaller hidden layer to accomplish the compression process. Then a decoder will reverse the process. The backpropagation is one of the essential pieces of this puzzle. The previous is responsible for the learning process, and without it, our experiment and this proof would look completely different. We decided to use Root Mean Square Error for this experiment.

$$RSME = \sqrt{\frac{\sum_{n=1}^{N}(x_i - y_i)^2}{N}}$$

The encoder contains a feature input layer, two fully connected layers with ReLU as activation functions, and a regression layer (Figure 3). Since we only use one EEG channel for this proof, the encoder has an input size of 500 vectors and reduces it to 75. The decoder does the reverse. It takes the 75 vectors from the encoder and expands it to 500. The decoder uses a feature input layer, a single fully-connected layer with a sigmoid for activation, and a regression layer (Figure 4).

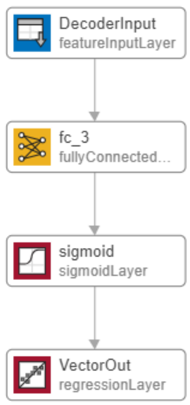

Figure 4 Decoder

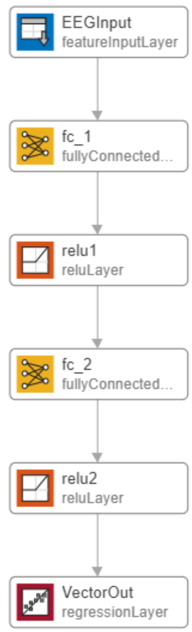

Figure 3 Encoder

The proof used a fully connected layer to convert the noise into vectors, then injected into the encoder. Since we do not want that code to learn, we set the learning rate factor and bias to zero [11]. This proof first passed the EEG data clean and then passed it with noise injected into the hidden layers. This subproject compared the input to the output. The closer the output graph resembles the input graph, the more robust the E/D pair are. As described above, the best-

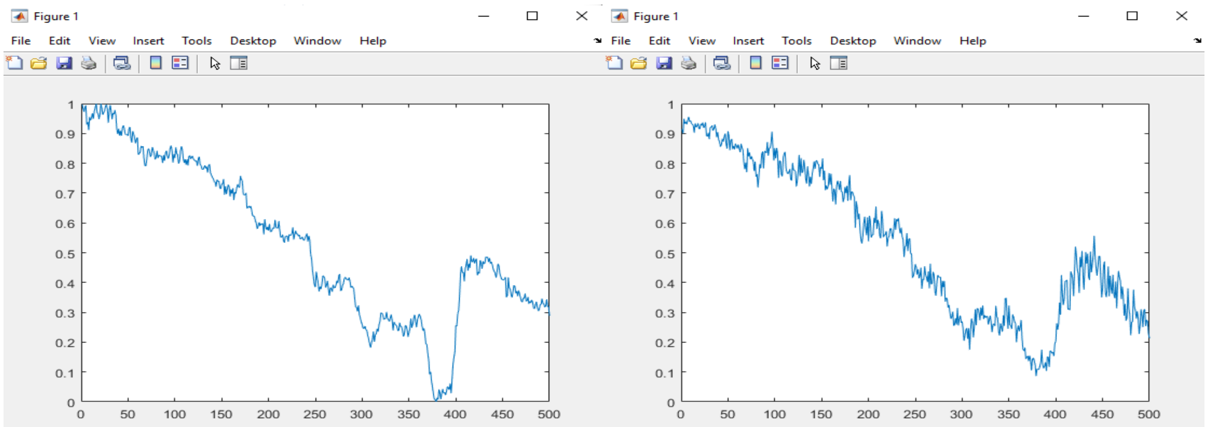

Figure 5 Sample encoder input (left) and decoder output (right)

performing E/D pair produced a signal close to the input (Figure 5). This proof of concept demonstrated that training an encoder/decoder pair is viable for developing optimized compression for EEG Bluetooth transmission. As described in this proposal, the following steps will expand from one channel to 16, then 32 channel NI-EEG signals, and add the classification step. The above gives us the confidence to move forward with our research.

Dataset

This research needs a labeled multichannel EEG signal dataset acquired using an NI BCI. Preferably the NI BCI will contain 16 channels or more. The best dataset should come from a previous experiment. The previous is essential to have a baseline performance for the classifier.

I selected a dataset from the Patient Repository for EEG Data and Computational Tools [12]. These datasets are well-curated and contain various EEG data of various neurological conditions. The over-the-air deep learning-based radio signal classification data set from DeepSig [13] contains a repository of various radio signals that would interfere with Bluetooth signals. The algorithm used the previous dataset to inject noise and simulate transmission. This noise helped us test how robust the modeled encoder/decoder pair is. After injecting noise into the process, if the classifier can maintain the performance, that will prove the robustness of the model.

The best set of data is EEG signals transmitted via radio. Unfortunately, datasets fitting the precious description do not exist. This project is considering using a Generative Adversarial Network to construct a dataset repository for our and the scientific community's use. As more interest in the subject grows, this repository will be essential for future experiments.

Resources

Dr. Adriane Randolph has granted this project access to the KSU BrainLab and NI BCI equipment. Since 2007, the KSU BrainLab has worked to understand an individual's control of brain-based devices, design devices that improve quality of life, and assess the usefulness of brain-based applications in organizational settings. The lab's primary interface has been NI BCI devices. Dr. Adriane Randolph, the executive director of BrainLab, has agreed to allow this project to utilize the lab. We have access through the BrainLab to a 20-channel wireless EEG system that transmits data via Bluetooth from Advanced Brain Monitoring (X-24 system) and both an 8-channel wired EEG system from Gugertech and a 16-channel wired EEG system from BioSemi (ActiveTwo system).

This research will also need significant computing power since we will use resNet101 as a classifier. resNet is a deep neural network; previous experience has proven it is a resource hog. The lead researcher's RTX 3080 TI will not be enough to advance this research at an acceptable rate. Because of the above, this project will require access to KSU's High-Performance Computing (HPC) resources. HPC will allow us to perform the experiments in an acceptable time frame. Without the KSU HPC, this experiment must migrate to a cloud computing platform: Amazon Web Services (AWS). There is a waiting list to gain access to GPU resources at AWS. If we can use services like AWS, the cost will be prohibitive.

Data Analysis

We anticipate that the data we will gain access to will be already processed. It was part of a similar classifying experiment. To be sure, we will review the data and adjust if necessary. Removing excess channels and organizing the data into training, testing, and evaluation groups are the data manipulations we anticipate. We must also code how the algorithm will build the frames to pass to the E/D pair. We intend to use the lessons learned during the proof of concept and minimize issues during the experiment.

Research Plan

The research plan is in Table 1. The goal was to defend the resulting thesis by the end of July 2022. The durations below were estimates. Acquiring the required resources, pending Kennesaw State University processing time should run shorter than estimated. f the previous was true, it would help set up the experiments sooner and allow more time to run them. Ideally, I would like to start the writing process in May 2022, but the timetable in Table 1 is feasible.

Task	Start Time	End Time
Gain access to all resources	Week 1, Jan 2022	Week 2, Jan 2022
Data Analysis	Week 3, Jan 2022	Week 3, Jan 2022
Encoder	Week 4, Jan 2022	Week 4, Jan 2022
Decoder	Week 1, Feb 2022	Week 1, Feb 2022
Classifier	Week 2, Feb 2022	Week 2, Feb 2022
Run Controls	Week 3, Feb 2022	Week 3, Feb 2022
Run Experiment	Week 4, Feb 2022	Week 4, April 2022
Result Analysis	Week 1, Mai 2022	Week 4, Mai 2022
Write Thesis	Week 1 Jun 2022	Week 3, July 2022

Table 1 Research Plan

Significance of Project

If this project could develop a faster and more robust Encoder/Decoder pair, we would increase the processing speed of the NI-BCI EEG signal. In turn, he would increase the possible applications of NI-BCIs and improve the quality of life of locked-in patients. The speed at which current systems process NI-BCI signals has limited the application of this technology. Removing the wires without losing speed is the goal. We are looking at lighter, less cumbersome, and more ergonomic designs for NI-BCIs. The more comfortable the patient feels wearing the devices, the more they want to use them, and the longer they will wear them.

Research Results

First Approach

Per the research design in the methodology section, the modified GAN did an amazing job compressing and recovering the data. The proof-of-concept section demonstrated that the algorithm could process 500 data points reliably. This research attempted to make this technology viable in research and commercial applications by expanding the number of data points processed at a time. The GAN needed to handle 36 channels of continuous data while maintaining reliability and information integrity. Initially, this research attempted to aggregate 500 data points evenly from all 36 channels. We split the data into 35 groups of 13 data points. The f36th channel contained 14 data points. Since each channel had a frequency band, the code normalized the batch. Lastly, the model processed the batch. Problems arose in data integrity. After troubleshooting, I was unable to remove the unreliability issue. I theorized that normalizing the data from 36 channels of different frequencies designed to not interfere with one another creates a step pattern that the model could not process effectively.

$$x = \frac{x - x_{minimum}}{x_{maximum} - x_{minimum}}$$

Equation 1: Normalization equation

Second Approach

The research methodology included increasing the number of data points to rule out the possibility of the initial attempt failing due to the small data size per channel. The data size per channel was increased to 500 to address this, resulting in 18,000 data points. However, it is important to note that hardware limitations became a factor that may limit the progress of this research. The time complexity associated with neural networks is exponential, and increasing the number of data points by 36 folds surpassed the limits of my hardware resources.

Next, I applied the algorithm to organize and normalize the batch of 18,000 data points. However, this time the steps involved were much larger due to the increased data size. After several runs, the same data integrity issue encountered in the initial approach resurfaced. The previous posed a challenge as retraining the model would be time-consuming and might not guarantee a resolution to the underlying problem. Consequently, we limited this research to modifying the data size collected per channel and the arrangement of the data to mitigate the data integrity issue.

Given these limitations, this research concluded that the step pattern resulting from the differences in frequency within the collected data caused the observed decrease in reliability. The previous suggested that the frequency variations presented a significant challenge to the reliable classification and interpretation of the user's intentions using the proposed algorithm.

It is important to acknowledge that addressing the data integrity issue and enhancing the system's reliability required further investigation and potential modifications to the algorithm. However, due to the hardware limitations and the constraints imposed by the observed step pattern, this study's scope is limited to the data mentioned above size and arrangement modifications.

These findings shed light on the intricacies and challenges associated with EEG data processing and classification, highlighting the need for ongoing research and innovation to overcome such limitations and improve the performance and reliability of Non-Invasive Brain-Computer Interfaces (NI-BCIs).

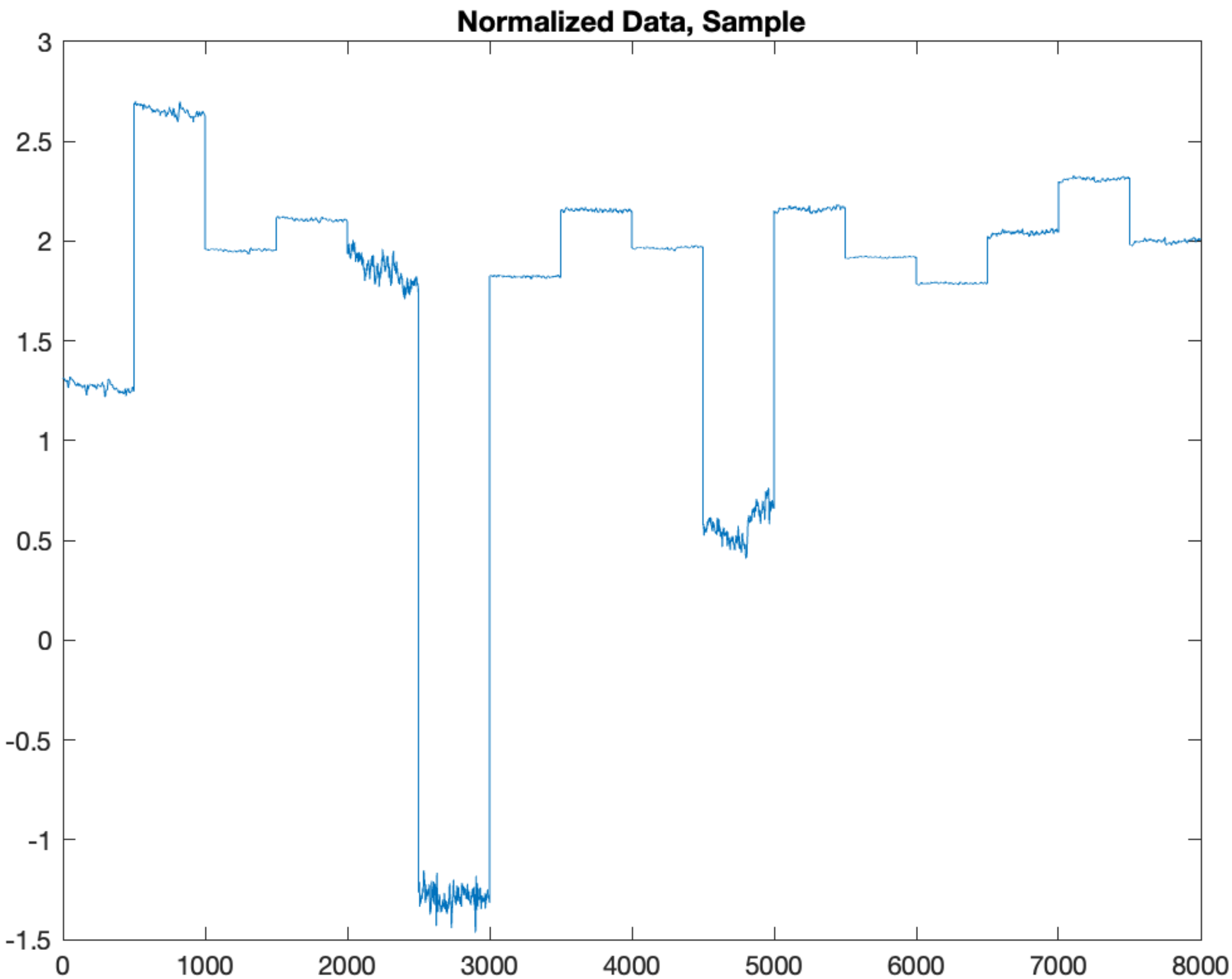

Figure 6: Sample of the step pattern

Linear Approach

This approach considered passing 500 data points through the model to eliminate the step pattern observed in the data. We designed the algorithm to process 500 data points per channel individually sequentially. While this approach significantly slowed down the data throughput of the technology, it effectively eliminated unwanted steps and alleviated hardware concerns. Additionally, this research aimed to test the viability of implementing this design in a small computing form factor, considering the future application of the technology as a wearable device. The researcher aspired to lean the technology to prevent user exhaustion or discomfort.

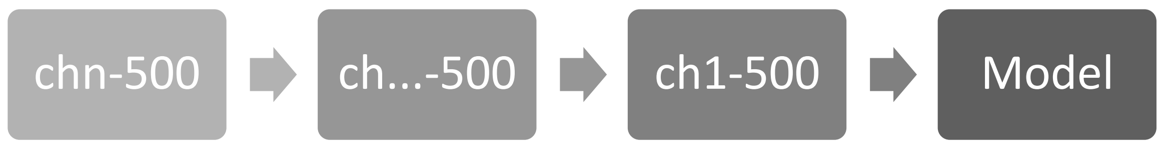

Figure 7: Linear approach

The proposed method involved processing 500 data points, as demonstrated in the proof-of-concept. In the linear process, the code took 500 data points from each channel and passed them individually, one at a time, as shown in Figure 6. Although this approach was slower than other methods, it offered simplicity and eliminated the need for a complex reassembly algorithm after the decoder stage. Straightforward code implementation could reassemble each channel's data points, preparing them for presentation or further analysis.

By adopting this approach, the research aimed to strike a balance between data processing efficiency and eliminating unwanted artifacts, ensuring the data's integrity and reliability. The goal was to optimize the algorithm for real-time performance, enabling seamless integration into wearable devices while maintaining a user-friendly experience.

This approach demonstrated the potential of addressing the step pattern issue by sequentially processing smaller batches of data. That offers a simpler implementation, reducing computational complexity and eliminating the need for complex reassembly algorithms. The previous could be advantageous for real-world Non-Invasive Brain-Computer Interfaces (NI-BCIs) applications. Further evaluation and refinement of this approach should be conducted to assess its performance, throughput, and compatibility with different hardware configurations.

The findings from this research would contribute to advancing the development of lean and efficient NI-BCI systems, facilitating more natural and intuitive interaction between users and technology, ultimately enhancing the user experience and enabling wider adoption of brain-computer interface technologies.

Parallel Approach

This approach incorporated parallel processing techniques to increase the transmission speed of the system. Instead of processing individual data batches sequentially, the algorithm now processed multiple data batches simultaneously. As a result, a larger packet containing multiple batches was transmitted to the decoder, as depicted in Figure 7. However, this approach introduced additional overhead and required a reassembly algorithm after decoding. The code implementation included labeling each batch before transmission and ensuring proper organization and synchronization of the batches.

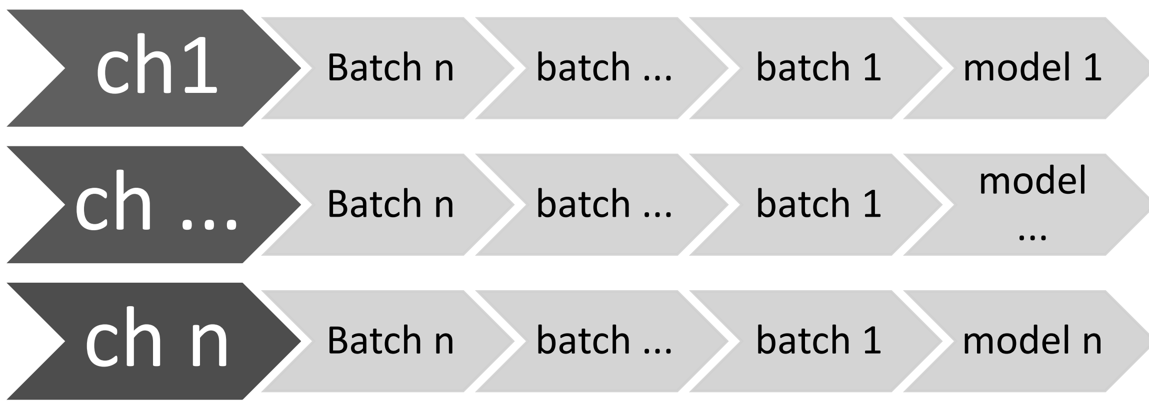

Figure 8: Parallel Approach

The reassembly portion of the code was responsible for reconstructing each channel from the received batches and preparing them for subsequent presentation or analysis. This step involved efficiently merging the data from the individual batches and ensuring the correct alignment and arrangement of the channels.

This approach increased the size of the packet transmitted, thereby reducing the queue of individual batches and optimizing the transmission efficiency. This research proposed the aggregation of all the first batches for each channel before transmission. This aggregation was essential for presentation purposes, as it facilitated the job of the presentation layer in showcasing apparent live data. By transmitting larger packets with aggregated batches, the system could provide a smoother and more continuous stream of data to the presentation layer, improving the user experience and reducing latency in visualizing the interpreted brain signals.

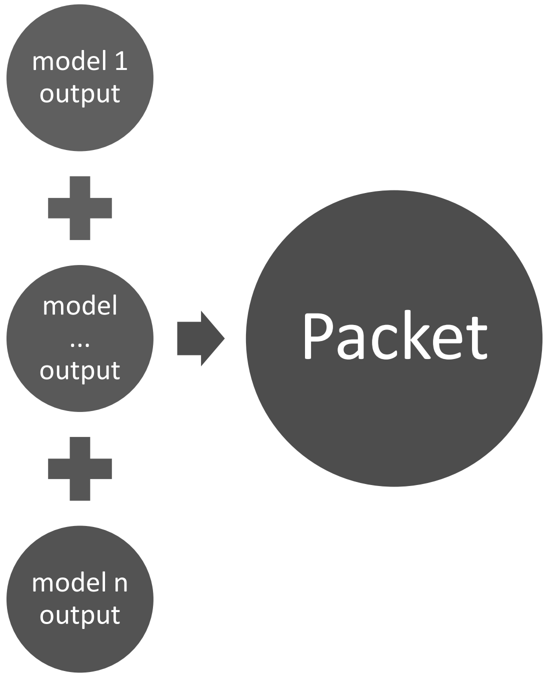

Figure 9: Batch Assembly

The proposed methodology recognized the significance of real-time presentation and aimed to streamline the transmission process to support efficient data visualization. By organizing and aggregating the initial batches for each channel, the system could present a coherent and visually coherent representation of the user's intentions. This approach contributed to the seamless integration of the Non-Invasive Brain-Computer Interface (NI-BCI) technology into various applications, such as user interfaces or control systems, where the presentation of apparent live data is crucial for effective interaction.

Comparison

The parallel approach with an accuracy of 97% did not achieve the highest. The linear approach had the highest accuracy of 98% but was much slower than the parallel approach. The first approach plateaued at 65%. The second approach plateaued at 55%. I used the timeit() function form MATLAB to get the average duration for each approach. The first approach had the fastest processing time of 0.0043 seconds. The parallel approach had the second fastest time with 0.752 seconds. The second approach had the third fastest time with 0.1550 seconds. The linear approach had the fourth fastest time of 1975 seconds.

Approaches	Accuracy	Duration
First	65%	0.0043s
Second	55%	0.1550s
Linear	98%	0.1975s
Parallel	97%	0.0752s

Table 2: Approach accuracy table

Further refinement and evaluation of this approach should be conducted to assess its impact on transmission speed, latency reduction, and overall system performance. The findings from this research will contribute to developing efficient data transmission strategies and improving the real-time presentation capabilities of NI-BCIs, advancing the field and fostering more practical applications of brain-computer interface technologies.

Conclusion and Future Works

In conclusion, this thesis paper explored the potential of Non-Invasive Brain-Computer Interfaces (NI-BCIs) to enhance human-computer interaction and improve the quality of life for individuals with severe physical limitations. These technological advancements paved the way for developing NI-BCIs, which utilize electroencephalographic (EEG) signals to detect and interpret user intentions.

Throughout the study, we identified the limitations and challenges associated with BCI technology. These included issues related to wires, noise, and the need for invasive procedures in certain cases. Such limitations have hindered the widespread adoption of BCIs beyond highly regulated medical studies and novelty applications.

To address these challenges, this research focused on developing an effective Encoder/Decoder (E/D) algorithm using machine learning techniques, particularly borrowed techniques from GANs. The goal was to minimize the number of bytes transmitted and ensure robustness against data degradation, enabling efficient transmission and classification without compromising speed and accuracy.

The proposed research aimed to train an E/D pair, leveraging machine learning to self-adjust and isolate essential data for classification. By doing so, the study sought to unlock specific applications of NI EEG BCIs, such as speech synthesis and seamless control of mobile devices, thereby improving the quality of life for individuals who are locked in.

The research plan outlined in this thesis paper includes a detailed methodology, research design, and dataset overview. By conducting experiments and modifying existing machine learning techniques, the study demonstrated the feasibility of developing an optimized E/D pair capable of effectively transmitting and classifying EEG signals over Bluetooth.

The implications of this research were significant, as it has the potential to revolutionize BCI technology and expand its applications beyond medical contexts. The successful development of a robust and efficient E/D algorithm could pave the way for more intuitive human-computer interfaces, empowering individuals with severe physical limitations to communicate and interact with their environment more seamlessly.

In conclusion, this thesis paper contributed to the ongoing advancements in NI-BCIs and set the stage for further research and development. This paper favored the parallel processing approach described in the methodology section. More research opportunities exist to explore allowing technology to figure out the best way to communicate large amounts of data with limited resources.

By harnessing the power of machine learning and addressing the limitations of current BCI technology, this study strived to unlock new possibilities and improve the lives of individuals who greatly depend on intuitive and non-invasive interfaces.

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