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

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ABSTRACT

This project demonstrates a proof of concept for developing a means to remove the wires from Electroencephalograph (EEG) Brain to Computer Interface (BCI) systems while maintaining data integrity and increasing the speed of transmission. This paper uses Machine Learning techniques to develop an Encoder/Decoder pair. The Encoder pair learns the important information from the analog signal, reducing the amount of data encoded and transmitted. The Decoder ignores the noise and expands the transmitted data for further processing. This paper uses one channel from an EEG-BCI system and organizes the analog signal in 500 datapoint frames. The Encoder reduces the frames to 75 datapoints and after noise injection, the decoder successfully expands them back to virtually indistinguishable frames from the originals.

Keywords

Electroencephalograph, Brain to Computer Interface, Machine Learning, Data Compression

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 for an intuitive system, hence the wide range of brain-computer interface (BCI) research. Brain-computer interface research has facilitated paralyzed people to move on their own accord, use a computer, and send email (Chaudhary, Taran, Bajaj, & Sengur, 2019). 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 (Fanfan, Randolph, & Suo, 2020). BCIs could be so much more. This study will focus on the Non-Invasive (NI) BCIs, which refers to technology that does not require surgery for its use.

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 (McFarland & Wolpaw, 2011). The system uses the classified intents and launches the appropriate sub-routines. These sub-routines then manifest as an action on a platform or the physical world (McFarland & Wolpaw, 2011). BCI's 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 extremely limited patients more available (Fanfan, Randolph, & Suo, 2020).

Based on previous experience and the literature review, some of the most significant limitations of BCI technology are related to wires and noise (McFarland & Wolpaw, 2011). 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 blinks. These noises affect our ability to classify intent, especially motor imagery (MI) applications (McFarland & Wolpaw, 2011); they make classification slow and inaccurate. The previous can increase the user's frustration and reduce concentration (Fanfan, Randolph, & Suo, 2020). 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 (Neuralink, 2021) 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.

To eliminate the wires, the encoder/decoder (E/D) algorithms must minimize the number of bytes to compromise the transmission speed. 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, *is it possible to use ML to model and optimize an E/D pair that can transmit over Bluetooth without compromising speed and classification?* This study will try to answer these questions.

This research will consider using borrowed techniques from Long Short-Term Memory (LSTM) and other Deep Neural Networks. This research will especially focus on the backpropagation of these machine learning techniques. This experiment must modify these techniques to fit our goals. These ML techniques are not one size fit all and will be at the core of the success of this project.

Suppose we can maintain or increase the speed of transmission and classification accuracy. In that case, we will unlock specific applications of NI EEG BCIs, significantly improving the quality of life of locked-in patients (Fanfan, Randolph, & Suo, 2020). For example, an NI EEG device may be used for speech synthesis or to control a mobile phone for more seamless communication efficiently.

We propose training an E/D pair. Machine learning techniques will self-adjust and isolate the crucial bites to classification. This triage will only codify and transmit what is needed. We outline in the research design subsection of the methodology how we plan to test the E/D pair.

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

LITERATURE REVIEW

In Fanfan et al. (Fanfan, Randolph, & Suo, 2020), 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 (McFarland & Wolpaw, 2011) and (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002), 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 utilization of electrophysical signals were described, and the critical problems in BCI-based control and communication systems were highlighted.

(McFarland & Wolpaw, 2011) 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 parts of the body for triggering neuronal activities in particular brain regions that are linked with the movements

In (Chaudhary, Taran, Bajaj, & Sengur, 2019), Their team explained the role of BCIs in communication and motor rehabilitation. This study discussed BCIs for communication in individuals suffering from locked-in disorder 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 (Asieh, Mohammad, & Deniz, 2018), 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 (Rasheed, 2021), 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 (Müller, et al., 2008), the ML approach was proposed for EEG signal analysis in real-time. It even discussed the significance of ML schemes for mental condition monitoring and EEG-oriented BCI applications. The previous has the potential to assist in as a diagnostic tool.

In (Lotte, et al., 2018), 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 (Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007), They reviewed different classification approaches for EEG-oriented BCIs. This study reviewed five classification approaches, namely, 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 are very few literatures available on EEG radio transmission. This project is at the forefront of exploring better algorithm 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.

RESEARCH DESIGN

We will use machine learning techniques to develop 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).

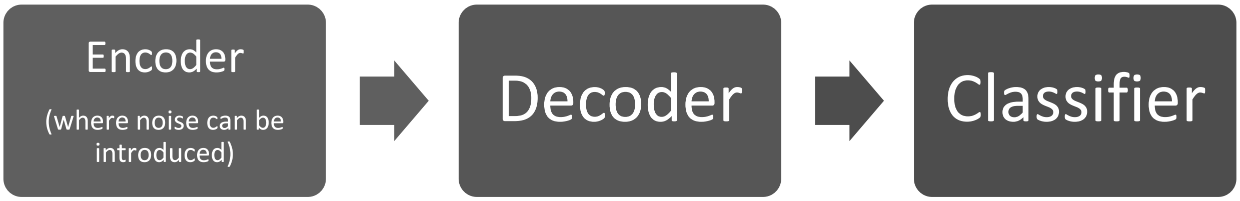

Figure 1 Algorithm Structure

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 better understand the performance of the E/D pair (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.

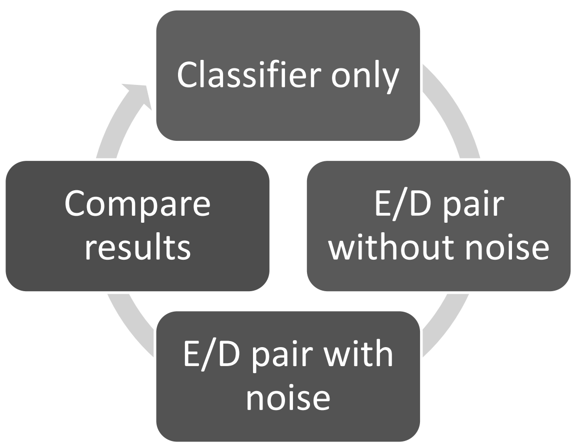

Figure 2 Experiment Group

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

A proof of concept was initiated 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 down in a hidden layer, and expand them back to their original size as accurately as possible (Blankenship, 2021). The idea is to take the input vectors and process them 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 followed by two fully connected layers with ReLU as activation functions and, finally, a regression layer (Figure 3). Since we are only using 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).

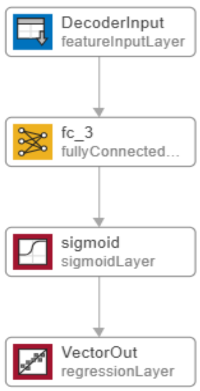

Figure 4 Decoder

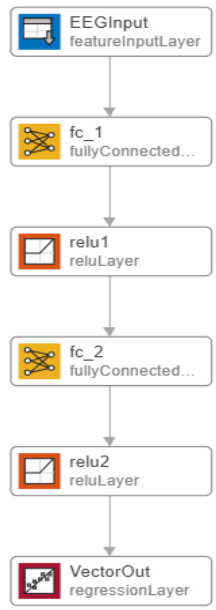

Figure 3 Encoder

The proof used a fully connected layer to convert the noise into vectors, then injected it into the encoder. Since we do not want that code to learn, we set the learning rate factor and bias to zero (Blankenship, 2021). This proof firstly passed the EEG data clean and then passed it with noise injected into the hidden layers. This subproject compared the input is 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 performing E/D pair produced a signal very close to the input (Figure 5). This proof of concept demonstrated that training an encoder/decoder pair is viable to develop optimized compression for EEG Bluetooth transmission. As described in this

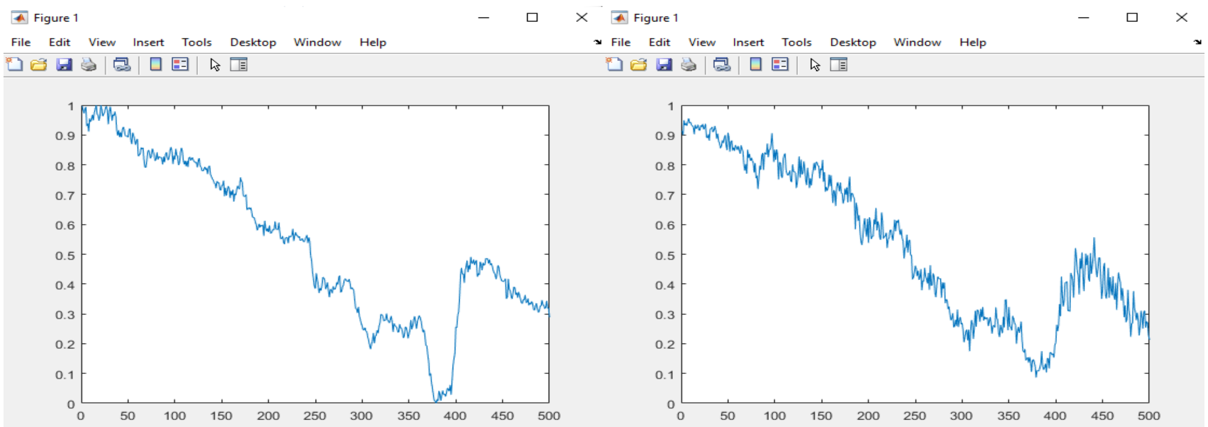

Figure 5 Sample encoder input (left) and decoder output (right)

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.

We plan to select a dataset from the Patient Repository for EEG Data and Computational Tools (Predict). 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 (DeepSig, 2018) contains a repository of various radio signals that could interfere with Bluetooth signals. The algorithm will use the previous dataset to inject noise and simulate transmission. This will help us test how robust the modeled encoder/decoder pair are. 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 are EEG signals transmitted via radio. Unfortunately, datasets fitting the precious description does not exist. This project is considering using a Generative Adversarial Network to construct a repository of dataset for our and the use of the scientific community. As more interest in the subject grows, this repository will essential for future experiments.

DATA ANALYSIS

We anticipate the data we will gain access to will be already processed. It was a 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.

SIGNIFICANCE OF PROJECT

If this project can develop a faster and robust Encoder/Decoder pair, we will increase the processing speed of the NI-BCI EEG signal. The previous, in turn, will increase the possible applications of NI-BCIs and lead to the improvement of 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. Then, 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, the longer they will wear them.

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