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Utilizing Deep Neural Networks for Brain–Computer Interface-Based Prosthesis Control*

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Abstract

Limb amputations affect a significant portion of the world's population every year. The necessity for these operations can be associated with related health conditions or a traumatic event. Currently, prosthetic devices intended to alleviate the burden of amputation lack many of the premier features possessed by their biological counterparts. The foremost of these features are agility and tactile function. In an effort to address the former, researchers here investigate the fundamental connection between agile finger movement and brain signaling. In this study each subject was asked to move his or her right index finger in sync with a time-aligned finger movement demonstration while each movement was labeled and the subject's brain waves were recorded via a single-channel electroencephalograph. This data was subsequently used to train and test a deep neural network in an effort to classify each subject's intention to rest and intention to extend his or her right index finger. On average, the employed model yielded an accuracy of 63.3%, where the most predictable subject's movements were classified with an accuracy of 70.5%.

1 Introduction

Every year approximately 185,000 limb amputations occur in the United States of America [11]. The loss of a limb can be life changing; once menial activities quickly become laborious and nontrivial. Limb loss can also be accompanied by mental health issues. Those who have recently lost a limb often report depression associated with the new impairment of mobility [8]. The loss of a limb can drastically change one's lifestyle and can be extremely discouraging.

The difficulty with adjustment to life after limb loss is directly related to loss of capability, both agile and tactile. What an amputee's lost arm was once able to feel and achieve through the intricacies of the biological brain-arm network is lost. The once unacknowledged, seamless tie between the arm and the brain becomes something mourned, especially in light of the sensation of the limb's persisting presence. Many amputees report feeling the limb's continued presence even after the limb is gone [8]. This sensation is an artifact of the brain's neuronal mapping associated with limb movement. These sensations can be painful or painless and can include sensations such as perception of movement, touch, temperature, pressure, vibration, and itch [15]. So the brain still possesses a capacity to process these stimuli that were once associated with the limb even after it is gone. This phenomenon seems to suggest that brain still possesses the toolkit necessary to re-establish connection with a limb, organic or not, in the place of the lost limb, given that the limb possesses compatible sensing and actuating mechanisms.

Efforts to develop such a device could be established by first developing rudimentary technologies that accurately interpret user intent. An attempt is here made to procure and investigate the viability of such a technology capable of detecting user intent to rest and extend his or her right index finger through the use of single-channel electroencephalograph (EEG) and intelligent classification of intention via a deep neural network (DNN).

2 Background

2.1 Brain–Computer Interfaces

There currently does not exist a prosthesis that can accurately and precisely report sensations and execute actions to the same functional degree as an organic human appendage. This is largely because of the limitations of today's brain-computer interfaces (BCI). The human brain possesses approximately 100 billion neurons, a number that makes the prospect of reading from each individual neural pathway in parallel daunting [6]. There has been a notable trend in BCI development over the past few decades, specifically, every seven years, the number of neural pathways that can be simultaneously monitored using a brain-computer interface doubles. Even with this exponential growth, progress is still currently slow; according to this model, reaching a point where all 100 billion neural pathways can be read simultaneously will take electrophysiologists nearly 220 years [16]. While this does provide hope for the amputees of tomorrow, it does beg the question of whether or not an alternative is currently in reach for amputees today. If such an alternative to total neural monitoring does exist it would surmount one of the biggest obstacles on the path to a more "seamless" prosthesis that senses and actuates with high levels of accuracy and precision.

Approaches toward the development of advanced prostheses and a greater understanding of the interaction between brain and limb have been rife. One such study sought to investigate the viability of functional electrical stimulation, through multi-electrode arrays implanted in the motor cortices of two rhesus macaque monkeys who underwent temporary limb paralysis. This method worked with the monkeys being able to control the flexion of four of their forearm muscles. During these trials, the monkeys effectively doubled their maximum voluntary wrist flexion force and were able to follow visually displayed force targets at two-thirds the speed of an unimpaired subject [13]. Studies such as this one support the viability of invasive BCIs (i. e., electrocorticography, or ECoG) for use in the prosthetics of tomorrow. Further studies utilizing invasive BCIs have exhibited that the motor cortex can form a stable neural representation for neuroprosthetic control, meaning that the brain exhibits a deft capacity for adapting to and cooperating with prostheses through the use of ECoG [5]. In one notable study, three test subjects (one with a neuroprosthetic arm) were trained to control the amplitude of beta rhythm recorded over the frontal areas of the brain using EEG. After six months of regular training, subjects were able to use these controlled signals to move a cursor to targets on a computer screen with greater than 90% accuracy. Additionally, the subject possessing a neuroprosthesis was able to use these signals to effectively grasp objects with his prosthetic arm [7]. In contrast to the six month training period that subjects underwent in the above study, another study utilizing EEG included the recording and power spectral analysis of neural signals from a single subject with an implanted neuroprosthesis over a three day training period. During this short time the subject was able to develop a stable neural representation that allowed him to consciously switch between grasp phases of the lateral grasp that his prosthetic provided. Using this developed ability, he was ultimately able to move a simple object from one place to another [10]. In other studies, researchers have used EEG signal mapping to send appropriate RF command signals to a prosthetic hand or have utilized support vector machines (SVM) to accurately predict the right or left-handedness of intended hand movement in subjects [12, 1].

2.2 Deep Neural Networks

The first computational model for an artificial neural network was presented by Warren McCulloch and Walter Pitts in 1943 [9]. In 1958, Frank Rosenblatt built on top of this work to develop the perceptron, an algorithm for pattern recognition [14]. Paul Werbos later developed a backpropagation algorithm that allowed these perceptrons to be layered, ultimately yielding the rudimentary model used for computing with artificial neural networks today [17]. A more modern major development in this field has been the development of deep learning, an idea first introduced in 1986 by Rina Dechter [4].

Recently there has been a resurgence of deep learning because of its uncanny in ability to classify data such as images and speech compared to more classical classification methods such as the SVM [3]. In an effort to capitalize on this machinery's ability to interpret digital signal data, methods are here employed in an effort to isolate and detect subjective intent based on brainwave signals collected from the subject's scalp.

3 Methodology

3.1 Data Collection

This study utilized electroencephalograms from five right-handed subjects, four male, one female. Each subject was connected to an EEG device, the Biopac MP36, via a single channel and had his or her brainwaves subsequently recorded for five trials, each three minutes in length. The electrodes were affixed to each subject's scalp using Elefix conductive EEG paste at F_Z, C_3, and C_4, as seen in Figure 1. This configuration choice was based on existing literature regarding optimal EEG electrode placement for the detection of subjective hand movement [2].

During each trial, subjects were told to mimic a video displaying a moving right index finger. The index finger executed one event per second in a predefined, looping sequence of events. As the subject replicated the movements of the right index finger on-screen, each event was automatically labeled in time. The sequence of finger-movement events used during this experiment was rest (R), rest to extension (RE), extension (E), extension to rest (ER), rest (R), rest to flexion (RF), flexion (F), and flexion to rest (FR). Because of the apparent doubled concentration of R events, only half of these, Rs preceding REs, were retained for final experimental analysis. This slight modification ensured that all events were equally represented in the training set, discussed in the next section. All data was collected in accordance with the collection procedure approved by our university's institutional review board for human subjects research.

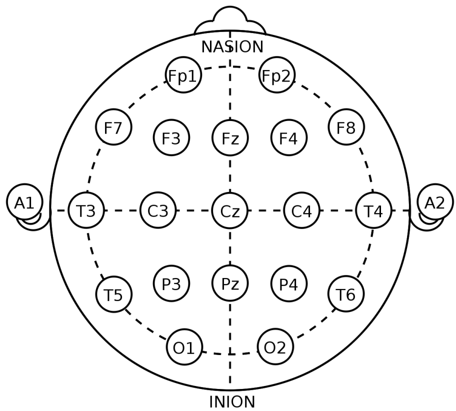

Figure 1: Standard EEG electrode placement; electrodes were placed at F_Z, C_3, and C_4.

3.2 Data Analysis

Signal data was collected at 500 Hz and events were labeled in the Biopac proprietary data analysis software, then subsequently exported and fed into a Python script where the signals were graphed and analyzed. Subsequently, the power spectral density (PSD) of each was calculated and plotted for exploration. In order to eliminate unnecessary information in the PSD data, a random forest classifier (RFC) was employed to rank PSD data points in order of significance. Using this information, researchers found that the frequency band that lent the most insight into subject intention was from approximately 12.76 Hz to 30.85 Hz. This information was used to inform which elements in the PSD data vector would be retained for training and testing the learning models.

Figure 2 depicts the retained portion of the power spectral density of both events. This retained portion was then processed using principal component analysis (PCA) to further reduce the data down to two dimensions, a feature vector size that was found to yield the best prediction performance. These labeled feature vectors were then used to train and test an SVM employing a radial basis function, and then a DNN utilizing the topology depicted in Figure 3. Training and testing was executed using k-fold cross validation where, for each subject, each model was trained on four of the subjects trials and then used to predict the held-out trial. The average accuracies of each of these classifications can be seen in Table 1 of the results section.

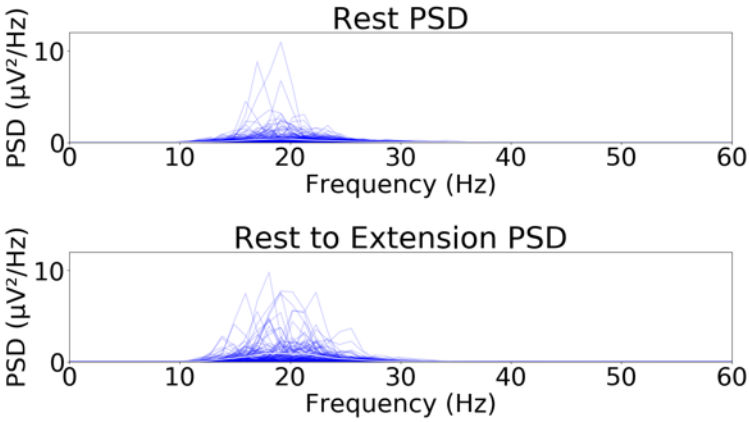

Figure 2: Filtered power spectral density of the subject brain signals.

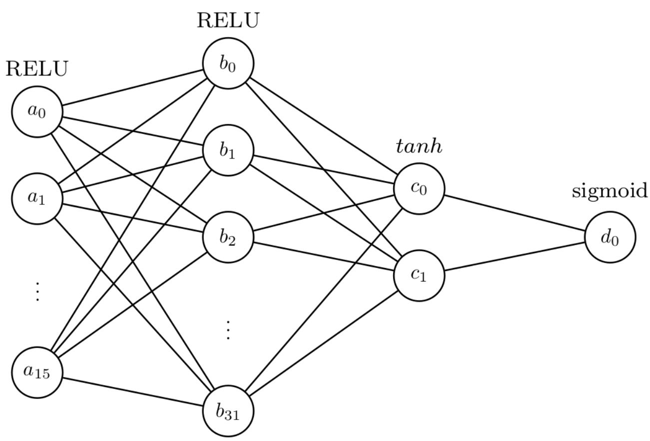

Figure 3: DNN topology with RELU input, RELU and *tanh* densing, and sigmoid output layers.

4 Results

Table 1 depicts the prediction accuracies generated by the DNN and the SVM. The average DNN classification accuracy across subjects was 63.3% and the average SVM classification accuracy across subjects was 62.4%. The best prediction accuracy across subjects was for the classification of subject B's inten-

Subject	Classifier	
	DNN	SVM
Subject A	0.600	0.586
Subject B	0.705	0.714
Subject C	0.627	0.609
Subject D	0.570	0.570
Subject E	0.664	0.641
Mean	0.633	0.624

Table 1: Per-subject and mean classification accuracy by classifier type.

tions where the DNN achieved an accuracy of 70.5% and the SVM achieved an accuracy of 71.4%. The t-value associated with these results was $t = 1.52$ and the p-value was $p = 0.203$, so the predictive accuracies of the SVM and DNN were not statistically significantly different from each other.

5 Conclusions and Future Work

Due to the complexity of this problem and the minimalist approach to brain signal sensing employed, the less-than-ideal results of this project were not entirely surprising. While the method of detecting subjective intention to rest or extend one's finger used here may not be practical, the results of this experiment beckon several other approaches to be explored in future work. These include incorporating the use of electrocardiography and oculography channels for artefact removal, adding more EEG channels, or utilizing an action, such as wrist flexion, that evokes a greater activation potential and repeating the process described here once more.

The implications of EEG-based intention detection beyond basic prosthetics are far-reaching. If further work reveals that non-invasive EEG monitoring can reliably yield subject intention or specific brain activity, technologies could be developed that support BCI-based control of mechanical and electrical systems. This would enable smart home network technology that would allow quadriplegic individuals to be able to perform household tasks such as opening doors, using the restroom, cooking, and cleaning without the need of human assistance.

Further research into BCI-based detection of other parameters describing an individual's state could be utilized to promote human safety. For example, driver wakefulness could be monitored to prevent traffic accidents by providing drowsiness warnings. Additionally, such a technology could be used by physicians to telemetrically monitor patient health. As medicine continues to become a more data-oriented profession, such a monitoring system could prove to be an invaluable diagnostic tool. If this technology were to be effectively harnessed, it would have the potential to revolutionize assistive and medical technology and drastically impact the way that humans and machines typically interact.

Acknowledgements

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