Neural Data Feature Extraction for Improved Machine Learning Kinematic Prediction of Intended Movement of Phantom Limbs

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***Abstract*—The long-term goal of this research is to improve neural data feature extraction to improve machine learning predictions for kinematic movement in the phantom limb of amputee individuals. The number of Americans with limb loss is currently 1 in 190 and expected to double by 2050. Electrical properties of neuron communication and the basic nerves that control muscle movements are still present in the residual limb of amputee individuals and can be utilized to predict kinematic movement. Results showed that exploring the realm of neural data feature extraction can lead to improvements in kinematic predictions which has the potential to improve intuitive control of prostheses. Within the results, the second neural feature resulted in a better general relation to the kinematics movement. Both finger and wrist performance metrics had statistically significant results between the two neural features and generally positive feedback was gathered about these performance metrics. The results provide a stepping stone in neuroprostheses towards achieving more intuitive bionic hand control with better kinematic predictive models. The algorithm and results may also be applied to adjacent fields, such as the development of other assistive devices in disease diagnosis for diseases such as Parkinson's.**

***Index Terms*—Neural Feature, Kinematic Predictions, Machine Learning**

I. Introduction

Currently, nearly one in 190 Americans live with limb loss. This number is predicted to double by the year 2050 [1]. As the number of individuals with this neurological impairment is likely to grow, it is important that efforts are focused on creating more intuitive tools to help these individuals adjust and improve their quality of life. Current clinical standards of care for these individuals focus on addressing pain treatment, exercise therapy, and educating these patients and their caregivers [2]. Although those aspects are vital, there are limitations when it comes to activities of daily life or leisure activities, and community integration [2].

Traditional prostheses have often been a useful tool for individuals with limb loss to regain some control over their daily lives. For further improvement, due to the electric spike behavior between the human brain's primary motor cortex and the body's muscles, engineers can take advantage of the electrical communication from the brain to a lost limb to animate control over a prosthetic device, providing the patients with more flexibility and functionality. When a limb is lost, the majority of the nerve wiring and structures leading up to that lost limb are still intact and functional [3]. Information from the neural signals that are still active leading up to the limb can be utilized to predict the kinematic movement that would have occurred, leading to smarter information being added to the current state of prostheses.

The methods for collecting and interpreting motor signals continues to be with the use of electrodes. Different types of electrodes may be used for different purposes. The most developed state-of-the-art method is with an implantable electrode array within the central nervous system to restore prostheses motor control and sensory feedback [4]. However, this can be a risky procedure since it involves brain surgery.

The objective of this paper is to develop different methods for neural feature extraction using an implanted device in the peripheral nervous system, which provides a less risky approach to more intuitive prostheses. This paper will explore how the neural data may be pre-processed to obtain better kinematic predictions when in conjunction with a machine learning model. The findings from this paper conclude that almost all the electrode recording channels showed statistically significant differences in their signal-to-noise ratio comparisons, except for the relation between electrode channels two and four. During pre-processing exploration, the second neural feature resulted in a better general relation to the kinematics movement. Both performance metrics, finger and wrist movements, had statistically significant results between the two neural features. Overall, positive subjective remarks were received by the individuals who reviewed the kinematics results.

II. Methods

The following section reviews the specifications of this study outlined through a variety of subsections, including participants, signal acquisition, feature generation, algorithm and evaluation, and statistical analysis.

A. Participants

The research data acquired within this paper was collected from a single, amputee participant. The participant had their left foot and forearm amputated thirteen years ago [4]. The participant is male and 57 years old.

B. Signal Acquisition

Within this study, two Utah Slanted Electrode Arrays were implanted in the median and ulnar nerve of the patient's residual limb. Each electrode array contained 100 microelectrodes. In addition to the devices, eight intramuscular electromyographic recording leads were implanted at locations aimed to measure the activity of different lower-arm muscles. Each of these leads had four electrical contacts, making a total of 32 recording channels. The raw data from these channels were passed through a series of filters and combined deferentially in 496 different combinations. Ultimately, the mean absolute value of the 528 channels (496 + 32) was calculated at a sampling rate of 30 kHz [4].

The recordings were collected while the participant tried to copy a set of previously decided movements with his phantom hand. The movements were shown to him with a virtual hand simulation. These movements tested different degrees of freedom, such as the individual movement of different digits and wrist movement. Each training movement consisted of 5-10 trials [4].

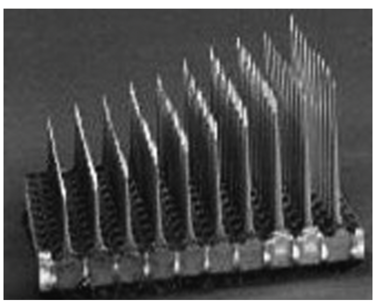


Fig. 1. The Utah Slanted Electrode Array is a neural recording microelectrode device that is implanted in the peripheral nerves. It has 100 shafts, where the metal electrodes are located at the tip, and it can record both spike events and ENG data. [5]

C. Feature Detection

From the given data, spike detection was conducted using negative threshold limits. For each channel under evaluation, a spike was detected when the waveform dropped below a custom threshold value. The spike was triggered using a negative threshold because extracellular neural signals begin with a negative development in the signal, therefore this allowed the triggered to be performed at the appropriate time such that the full spike data was captured in the proceeding time unit. The custom threshold values were determined by the analyzing team based on visual inspection of the filtered waveforms.

The signal-to-noise ratio of the spike waveforms were calculated individually by taking the summation across the waveform values and dividing it by the minimum threshold of that channel. Conceptually, this is because the minimum threshold of the signal can be viewed as the threshold that separates the targeted neural signals and the noise.

Two methods for isolating neural features were explored using the filtered data after spike detection was conducted. The first neural feature was determined by running a moving mean over the data for each of the five channels independently. The window for the moving average was set to 30k to match the sampling rate, and the mean was amplified to improve results.

The second method for isolating neural features was using the same implementation, but varying the combination of the given five channels to reduce the number of channels. The motivation behind this is to combine channels with similar neural spike data in order to create stronger indicators that correlate with kinematic movements. Channels were inspected visually and different combinations were explored. Channels were combined by overlapping the spike waveform data on top of each other. Ultimately, the best combination found was a reduction to three channels: channel 1 containing the combination of channels 1,2, and 4; channel 2 containing the original channel 3; and channel 3 containing the original channel 5.

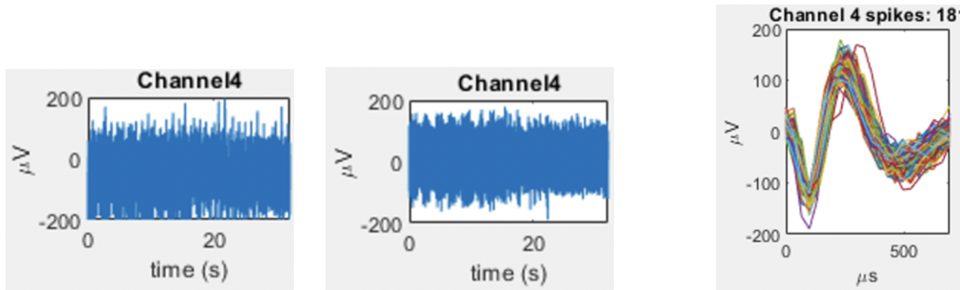
D. Algorithm and Evaluation

The neural network algorithm used in this study was a fully connected multi-layer perceptron with five layers. Each layer was followed by a $tanh$ activation function. The final layer was a regression layer. The learning rate was set to 0.01 and was run for five epochs.

Once the neural network was trained and predictions were made based on the test data, the performance of the network was evaluated with visual comparison, as well as computational comparison, of the predicted waveform and the true kinematics. The main visual traits that were inspected was if there was a rising activity that correlated with the kinematics and how strong the correlation is by comparing the amplitude of the waveforms. Computationally, the element-wise difference was taken between the true kinematics waveform and the predicted kinematics waveform.

E. Statistical Analysis

To begin the statistical analysis, the data was tested to detect any outliers and remove them when necessary. Then, a test of normality was conducted on the cleaned data for the wrist and digits kinematics for each neural feature extraction method. In addition, normality was tested separately for the SNR data from both neural feature methods. The normality tests revealed that all kinematic data was parametric and only SNR data was non-parametric, therefore, all the data sets were treated as non-parametric moving forward. The statistical analysis for the kinematic data was comparing two groups, for the two neural feature methods, and the data was determined to be unpaired. Therefore, Wilcoxon Rank Sum was used for analysis. Th statistical analysis for each kinematic movement of each neural feature had 233876 samples, corresponding to the number of points within the true kinematics and predicted kinematics waveforms. The SNR data was comparing ¿2 groups, for the multiple channel SNRs. Therefore, Non-parametric ANOVA and a Multiple Comparison Test was used for analysis. The SNR statistical analysis was performed on the first neural



a. Unfiltered Neural Data b. Filtered Neural Data c. Example Neural Unit Waveforms

Fig. 2. Waveform Results for a single example channel (channel 4).

feature method, meaning that the number of samples was the number of channels (5) times the number of SNR readings for each channel, which is effectively the number of spikes detected in each channel.

III. Results

A. All recording channels showed statistically significant SNR comparisons except for the comparison of channels two and four.

Within this experiment, the neural signals were recorded from eight intramuscular electromyo-graphic recording leads were implanted within an amputee participant at locations aimed to measure the activity of different intended lower-arm muscles in the phantom limb. The SNR values were calculated by taking the summation across each the waveforms and dividing it by the minimum trigger threshold of that channel. The SNR values ranged from $0.4 - 4.5$.

Fig. 3 displays the box-plot analysis comparing the SNRs for the five recodring channels. For the statistical analysis comparison, the SNR values were calculated using the channels in the first neural feature. The only two channels that did not hold statistical significance in their comparison were channels two and four.

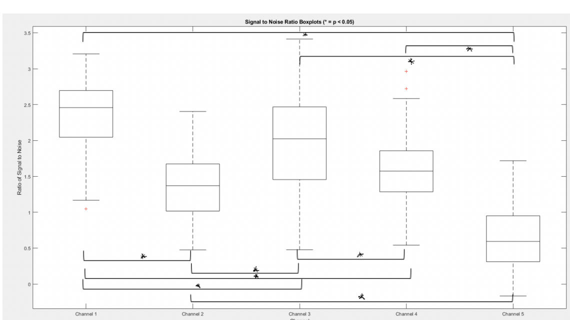


Fig. 3. Signal-to-Noise Ratio Box Plot for the five electrode channels. The $*$ indicators denote relationships with statistical difference, where $p < 0.05$.

B. Neural feature two resulted in a better relation to the kinematics.

The first neural feature was determined by running a moving mean over the data for each of the five channels independently. The window for the moving average was set to 30k to match the sampling rate, and the mean was amplified to improve results. The second method for isolating neural features used the same implementation, but ultimately combined some similar channels to create stronger indicators that correlate with kinematic movements. Channels 1, 2, and 4 were combined into a single channel, and channels 3 and 5 were left as independent channels, giving a total of three channels. Fig. 4a displays how the features looked in relation to the kinematics. Generally, we see a stronger correlation for neural feature two than in neural feature one.

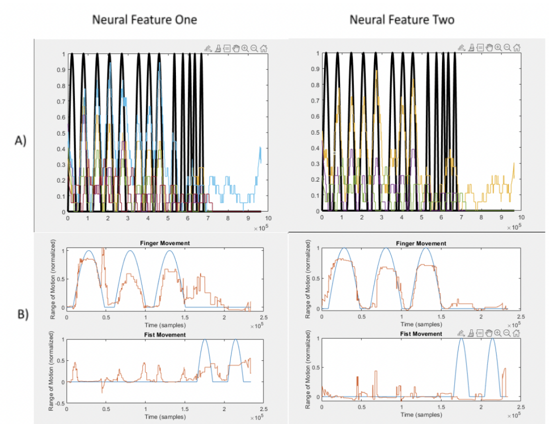


Fig. 4. A) Two subplots that show an overlay of the kinematics and neural features for neural feature one and two (left to right respectively). B) Two subplots containing kinematic predictions for the two neural feature methods. Each subplot shows the kinematic predictions for the finger movements (top) and wrist movements (bottom).

C. Both finger and wrist movement performance metrics had statistically significant results between the two neural features.

The two performance metrics used within this study were the kinematics of the finger movements and wrist movements. The true kinematics waveforms were compared to the predicted kinematics waveforms. Computationally, the performance was defined by taking the difference between the two waveforms to see how close their relationship is. Fig. 5 displays two subplots containing the box-plots for the statistical analysis of these performance metrics. Both performance metrics results in statistically significant outcomes where their p values were less than 0.05.

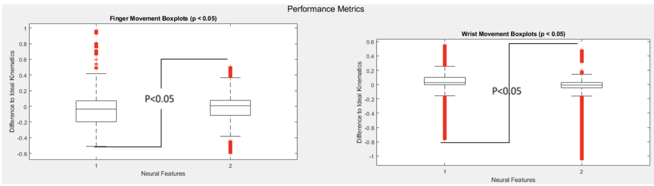


Fig. 5. Box-plots containing statistical analysis of the two performance metrics for finger and wrist movement. The two boxes in each box-plot represent the analysis for each of neural feature. A) Box-plot of finger movement (right plot). There was a statistical significance between the two neural features. B) Box-plot of wrist movement (left plot). There was a statistical significance between the two neural features.

D. Positive overall subjective remarks were received.

A disclaimer should be stated that remarks mentioned are subjective, but can still be useful information for the improvement of future experiments. With this in mind, generally positive feedback was received when reviewing the kinematic predictions. Fig. 4b displays an overlay of the kinematic predictions with the true kinematic intention waveforms. Individuals felt that finger movement predictions were better in the second neural feature and that wrist movements exceeded in the first neural feature. However, individuals also pointed out that the wrist movement prediction of the first neural feature had more noise and looks like it might predict more false positives than the second neural feature.

IV. Discussion

This paper's objective was to develop different methods for neural feature extraction using an implanted device in the peripheral nervous system, which would provide a less risky approach to more intuitive prostheses. It explored how the neural data may be pre-processed to obtain better kinematic predictions when in conjunction with a machine learning model. The findings from this paper concluded that almost all the electrode recording channels showed statistically significant differences in their signal-to-noise ratio comparisons, except for the relation between electrode channels two and four. During pre-processing exploration, the second neural feature resulted in a better general relation to the kinematics movement. The finger and wrist movements performance metrics had statistically significant results between the two neural features. Generally, positive subjective remarks were received by the individuals who reviewed the kinematics results.

Prior work has shown that an implantable electrode array within the central nervous system can be used to restore prostheses motor control and sensory feedback [4]. Prior work has also shown that a less intrusive approach using EMG neural signals may be used for prosthetic control as well [6]. In contrast, here we show that a middle ground is possible and an effective solution.

The work presented here builds off of prior works by gathering the best components of what has already been developed. Using a implantable device allows for more precision and data collection compared to an EMG signal and since it is implanted in the peripheral nervous system, the risks for surgery are not nearly as high as brain surgery. Also novel from this work is the methods for neural features to aid machine learning pre-processing.

Future work should replicate these findings with additional participants to analyze if the machine learning process needs to be a unique one for each participant or if it can be generalized. In addition, additional neural feature methods could be explored in terms of implementation. Lastly, replicating these findings with different types of machine learning models may also be beneficial for kinematic prediction improvements.

The work accomplished in this paper has a direct impact on the field of neuroprostheses towards achieving more intuitive bionic hand control with better kinematic predictive models. The algorithm and results may also be applied to adjacent fields, such as the development of other assistive devices in disease diagnosis for diseases such as Parkinson's. The predictions may even be reverse engineered to help aid in Parkinson's therapy. Clinically speaking, the development of this work provides a foundation for improvements in prostheses. Improvements in prostheses can significantly impact the quality of life for amputees, providing a better approach for daily tasks and independence.

V. Author Contributions

PTZ and EW designed and implemented the spike detection, the two neural feature extractions, and the SNR calculations. PTZ and EW did the statistical analysis of the results found in this report. JK determined the cut-off frequency and sampling rate of the butter filter for the neural data. JK developed their own second neural feature and ran the SNR calculations and statistical analysis based on their implementation.

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