Implementation of Gaussian Smoothing for Neural Feature Extraction

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***Abstract*—The long-term goal of this research is to improve neural signal decoding in order to more accurately predict kinematics from raw neural data. An Austrian study found that almost 50% of upper limb amputee prosthetic users reject their devices. The current myoelectric prosthetics have issues, such as some users finding it hard to control given that they are an "open loop" system - meaning they do not give sensory feedback. Many users have to undergo "EMG training" to learn how to produce the required signals for control. There is a need for more robust signal decoding and movement prediction. We developed a filter for the identification of neural features and subsequent prediction of specific kinematics. We found that convolution using an adaptable Gaussian window provides adequate smoothing without causing sparsity. Our first method of interpolation for smoothing was not able to produce any predictions, while the Gaussian window was able to produce over 140 accurate predictions. This technology has the ability to provide more robust prosthetic control and potentially reduce rejection due to inaccurate movements or inability to produce movements. This work can also provide a starting point for more custom signal filtering algorithms.**

***Index Terms*—neural decoding, signal filtering, myoelectric prosthesis, machine learning**

I. INTRODUCTION

The prevalence of amputations was 1.6 million in 2005, which is projected to double by 2050. Over 80% of amputations are caused by trauma, making them a sudden and severe ailment [1]. On top of this, almost 50% reject their prosthetic due to "'unpredictability' in the response of the prosthesis to muscle contractions" [2].

In order to use neural signals for meaningful control, the signals must be decoded. This decoding process includes signal processing, enhancement, selection and different algorithms to finally decode [3]. Neural decoding is essentially a classification problem, which is where machine learning comes in. There have been great advancements in the field of machine learning, but many of the neural decoding techniques are based on old, linear methods [4].

Recent work has started to introduce more nonlinear techniques, such as an adaptive spike sorting algorithms to address the issues seen from weak EMG signals or poor signal-to-noise ratios [5]. This technique has been shown to improve the precision and recall of spike sorting, which is a first step of neural decoding, and applies developments in machine learning to neural decoding.

In this paper, we aimed to develop a way to filter raw EMG data and extract neural features accurately to predict the kinematics of hand and wrist movements. We based our approach on popular machine learning techniques: interpolation and convolution. Both of these are widely used for machine learning, specifically in image processing. While recent work has shown more use of convolutional filters and machine learning [6], none that we have seen show the use of Gaussian smoothing. We first focused on interpolation, using a custom filter that added weights to the locations of spikes to proportionally smooth the signal. We then switched to using a Gaussian window with an adaptable length to perform convolution. The output of both filters was used to train the same, basic, feed-forward neural net. The Gaussian window filter performed significantly better in terms of filtered features and prediction outcomes.

II. METHODS

A. Participants

The participant was a healthy, 57 year old, male, with left-arm amputation and a Spinal cord injury (SCI). He was left arm dominant and the amputation occurred 13 years prior to the study [7].

B. Recording Hardware

The raw EMG data was recorded from two implanted Utah Slanted Electrode Arrays (USEAs). USEAs are microelectrode arrays with 100 electrode shafts on each. The electrode shafts are arranged on a 10x10 grid on a 4mm by 4mm base with varying electrode lengths (Figure 1). The arrays had iridium oxide tips and were implanted in the participants residual limb, in the median and ulnar nerves. Although 32 channels of recordings were produced, 6 channels were used in this paper. The sampling rate used during recording and analysis was 30-kHz. During recording, a 6th-order highpass Butterworth filter (cutoff 15Hz) and 2nd-order lowpass Butterworth (cutoff at 375Hz) were used [7], [8]. During processing, an additional filter of 500Hz was used.

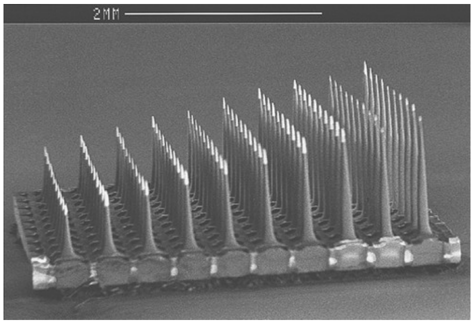

Fig. 1. The USEA is a neural recording device that can target varying depths of nerves given its variation in electrode shaft length. The tip of the array used was iridium dioxide and they were implanted in the medial and ulnar nerves of the participant (one array in each location). For perspective, a scale of 2mm is shown at the top. The base of the array is 4mm by 4mm. [9]

C. Signal Acquisition

During the data collection, the participant was told to mimic the movement of a virtual hand with his phantom hand. These movements included flexions/extensions of each finger, wrist flexion/extension, wrist pronation/supination and thumb abduction/adduction. For each movement, 5-10 trials were conducted [7]. For the purposes of this paper, only the grasping and wrist movements were used.

D. Spike Detection

We set a threshold for each channel to define a spike. The threshold for each channel was based on the standard deviation (STD) of the signal, multiplied by 4.25. The multiplication factor was based off of the proposed method in Petrantonakis and Poirazi [10], where they used STD multiplied by 2. We found that their value removed too many features, so we tested several other values and landed on STD multiplied by 4.25 as our threshold. We also found a significant repeat in spikes at the same time point. To address this, we identified the beginning and end of a spike event, found the middle spike occurrence and kept only that in our spike locations.

E. Signal-To-Noise Ratio

We used the collection of waveforms, which included the filtered neural signals 0.1ms before a spike location and 0.6ms after a spike location. Using this, we defined the signal to be the first 10 samples of the waveform and the noise to be the last 12 samples of the waveform. We used the amplitude of the signal and the standard deviation of the noise to find the signal-to-noise ratio: spike amplitude / noise standard deviation.

F. Neural Features

The first filter we created used interpolation to smooth the neural features. Using the filtered neural data (filtered with the additional 500Hz filter) and the information on the spike locations, we set custom weights for the spike locations (scalar of 5) and the length of the filter (500ms). We then applied a basic interpolation filter, with values of 1 everywhere besides the spike locations. This gave us values ranging from 0 to 1, with 1 being the highest spike and 0 everywhere there was no spike.

The second feature extraction technique built off the first, using the same idea of a window and weights for spikes, but addressed the issues of sparsity. This filter used a 100ms window and a Gaussian distribution to provide proportional smoothing.The window was then normalized to have the unit area and applied to each channel using the Matlab Conv function.

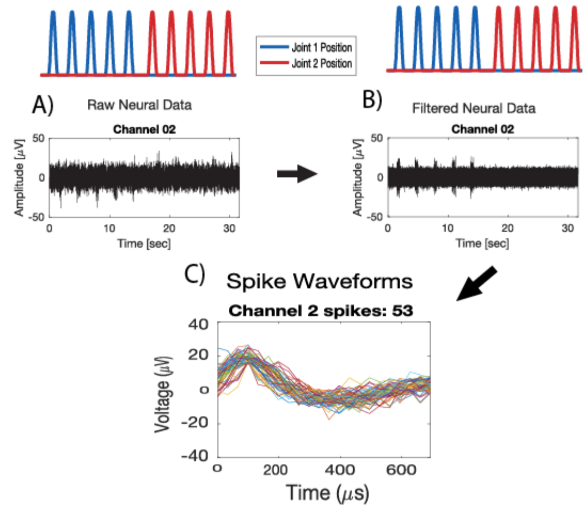

Fig. 2. A. Raw EMG signal from channel 2 of the implanted USEA. B. Filtered EMG data. The filter used a sampling rate of 30Hz and highpass filter at 500Hz. C. The resulting spike waveforms of channel 2's spikes. The spikes were founding using the spike detection algorithm in subsection D. The hand kinematics are shown in red and blue above the EMG data. No correlation is seen between the raw EMG and the kinematics. The filtered data begins to show correlation to the expected kinematics.

G. Algorithms

A neural net must be trained to make predictions on kinematics. The network used for the two techniques of neural feature extraction was the same. This is so direct comparisons could be made without additional variance. The network was an 11-layer, feed forward network. The input layer dimensions were 6x1x1, so adjustments were made to add padding to the feature array. There were then 5 fully connected layers with variations in the number of features, each followed by a hyperbolic tangent layer to work as the activation function and center the data between -1 to 1. The final layer was a regression output layer which produced the final predicted kinematics.

H. Evaluation

We used the prediction accuracy to evaluate the two feature extraction methods. We did not use learning metrics from the neural net, such as the loss and mean-squared-error because we were more concerned about the techniques ability to make meaningful predictions, not improvements in training. We defined accuracy as the prediction being 1 when the kinematics were 1. This allows us to have an understanding of which feature extraction method allows for more accurate decoding.

I. Statistical analysis

Statistical analysis was run on the SNR data. The data was non parametric, which was found by running an Anderson-Darling test (n = 6). We then performed an analysis of variance (ANOVA) (n= 6) and finally a multiple comparison test. For the multiple comparison, SNR for each channel was compared to each other channel (n = 36).

We tested the results of the networks for normality, then ran an unpaired t-test on the accuracy's of the networks for each kinematic (n = 4).

III. RESULTS

A. The SNR varied significantly between channels

The signals were recorded from the medial and ulnar nerves of the residual limb of an amputee. The SNR was calculated by defining the signal and noise and finding the quotient between the signal amplitude and noise STD. The average SNR per channel is shown in the table below. The results of the multi-comparison test are shown in figure 3. Of the 36 comparisons, 10 were found to have significant variation in their signal-to-noise ratio.

Channel and Average SNR

1	2	3	4	5	6
4.8302	4.1024	1.0298	0.8842	1.6230	3.3259

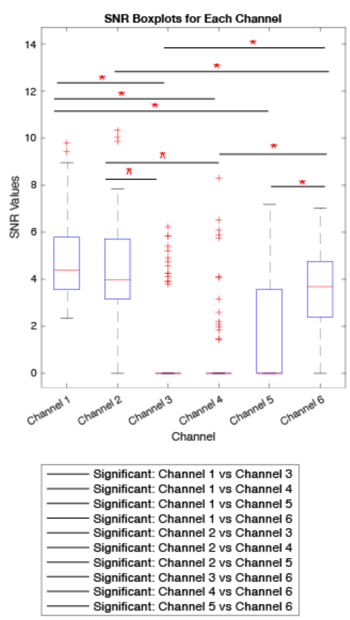

Fig. 3. There was a significant difference in the signal to noise ratio between the channels. The brackets and asterisks shown which channels had significant variation, as well as the legend below the plot. To find the differences, ANOVA for each channel (n = 6) was run. Then a multi-compare test for every channel combination (n=36). Significance was defined as p ¿0.05 and was found in 10 of the comparisons.

B. Only the Gaussian technique had meaningful decoding abilities

The first technique was interpolation using custom weights and filter size. The second technique was convolution using Gaussian smoothing with adjustments made for spike weights and window size. The first technique was able to produce good spikes (figure 4, part 1, A), but caused an issue of sparsity when all the other values were 0. The second technique addressed this issue. It kept the same ability to detect spikes and proportionally set the other values, instead of assigning only 0 (figure 4, part 1, B). While both techniques were able to get features that closely followed the kinematics of the hand (blue), both performed worse for the wrist (red).

C. Technique 2 accurately predicted the kinematics over 100x more than technique 1

To compare the performance of each feature extraction technique, we defined accuracy of the prediction to be when the model predicted 1 and the expected kinematic was 1. Technique 1 (interpolation) was able to get 1 accurate prediction for kinematic 1 (hand) and 1 for kinematic 2 (wrist) and had an overall accuracy of 3%. Techniques 2 (convolution) was able to get 140 accurate predictions for kinematic 1 and 10 for kinematic 2 and had an overall accuracy of 43%.

To further compare these techniques, an unpaired t-test was run on the accuracy of each technique for each kinematic (p = 9.9126e-5). The resulting counts of correct prediction and statistically significant differences are shown in figure 5.

D. Technique 2 could be used for real life prosthetic control

The significant difference between the two techniques is highlighted in figure 4, part 2. The poor performance of technique 1 (part 2, A) would cause significant issues for prostheses control and contribute to the high rejection rates. While technique 2 (part 2, B) does not perfectly predicted the intended kinematics, it has very significant improvement over technique 1 and could be used for meaningful control as is.

IV. DISCUSSION

The objective of this study was to develop a neural feature extraction technique that could be used to predict intended kinematics. We explored two techniques, interpolation and convolution. Only the convolutional technique using Gaussian smoothing had meaningful decoding abilities and could be used for prosthetic control. This technique had an increase in accuracy by over 100x. We also compared the signal-to-noise ratio between the recording channels and found significant variation between the channels (10 out of 36 comparisons).

Prior work has shown that other decoding techniques, such as regression based or Kalman decoding [9], share similarities with preprocessing techniques done for machine learning. These techniques have good results for decoding correlation to predicted movement.

To build off of this, we looked more into machine learning preprocessing to develop our decoding techniques. We applied two popular techniques in the field to neural data and kinematic predicting, which is a new direction for neural signal decoding.

Future work should continue to look into the field of machine learning and include continual learning techniques. At

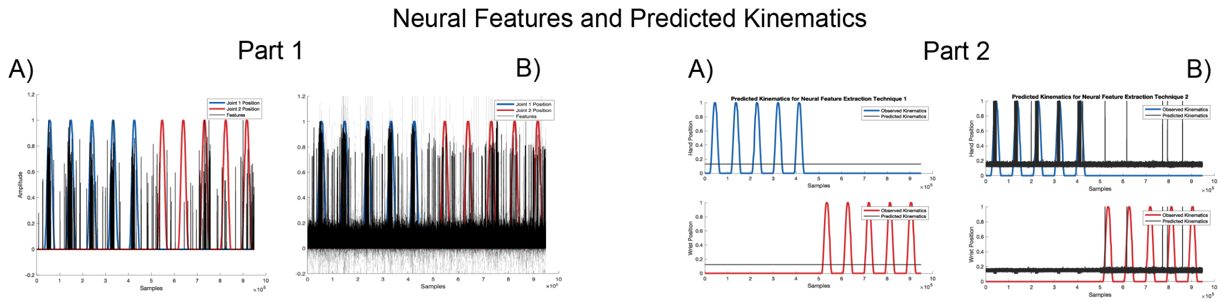

Fig. 4. Part 1: feature extraction for each technique. Part 1, A: feature extraction technique 1 (interpolation). Shows good ability to predict spikes, especially for the hand kinematic (blue), but causes sparsity. Part 1, B: feature extraction for technique 2. Much better ability to predict spikes and retains necessary values for training. Part 2 shows the predicted kinematics from training the neural net on each of the extracted neural features. Part 2, A: technique 1 predictions. Very poor prediction with very litter correlation. Part 2, B: technique 2 predictions. Overall decent predictions, especially for hand kinematics (blue).

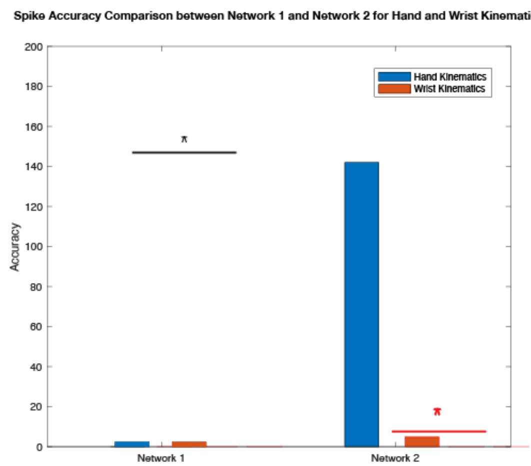

Fig. 5. Network 2 (trained on technique 2) had over 100 times more accurate predictions than network 1 (trained on technique 1). The brackets and asterisks show significant difference between each kinematic for each network. This was found by running an unpaired t-test on the accuracy (p = 9.9126e-5, n = 4)

the current time, each of these decoding techniques (the ones used in prior work and the ones in this paper) require training. Neural signals and systems are continuously changing, which can cause the decoders to become ineffective. The emerging idea of continual learning should be explored in terms of neural decoding. Additionally, in order to train a more robust decoder, neural recordings from more than one individual should be explored. This would allow for a more adaptable decoding algorithm that could be applied to more kinematics and also more people, again addressing the issue of having to retrain the decoders.

This work represents an overlap between neural signal decoding and machine learning. By helping to branch the disconnect between the fields, we have opened the door for many more applications of machine learning techniques in the field of neuroprostheses. To go along with this, we have shown how adjustments to decoding algorithms can significantly increase prediction accuracy, which can address issues of rejection for users. These results can also be applied to other aspects of neural decoding, such as using EMG signals for automation of everyday life. Rehabilitation following amputation is a vast field with many challenges, one being the rejection of prosthetics. The improvements shown in this paper help to address that issue by increasing the predictability of movement and can go a long way in improving the quality of life for amputees.

V. Author Contribution

RM wrote the code and defined the SNR, accuracy and analysis. CA found relating works. GO worked on improvements to the neural net structure.

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