Decomposition of Muscle Activity for Sensorimotor Neuroscience Proposal

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Contents

Executive Summary

Muscle movement is facilitated via the nervous system, which transports action potentials (electrical signals) from the brain to muscular motor units. The motor units pass these electrical pulses through motor neurons attached to muscle fibers, causing the muscles to contract. The net electrical charge of a muscle can be measured via electromyography, or EMG. EMG signals can then be decomposed into several individual electrical signals that can be ascribed to singular muscle units.

In this proposal, we attempt to recreate and improve the blind-source separation algorithm created by Negro, et al (2016) that decomposes action potential spike trains from EMG signals (Negro et al. 2016). As is, the blind source algorithm parses EMG signals in a single pass and incorrectly identified action potential peaks are manually removed post hoc. Ideally, the user would be able to remove these false positives from an early sample of the decomposition from which the algorithm would learn to avoid these mistakes in the rest of the decomposition.

The final product proposed is a Python package with two main components. The first component is the reconstructed decomposition algorithm, optimized for the UBC Kinesiology Lab use case. The second component is a visualization element that allows users to view the decomposed output of the algorithm.

Introduction

Motor commands, or the coordinated actions between the brain and nervous system, enable the muscular movement of daily life. As the human body ages or suffers from neuromuscular disorders, the brain's motor commands degenerate, leading to difficulty in mobility and communication. Thus, it is imperative to study motor commands and the neural system that facilitates movement in our bodies. In this proposal, we aim to create a Python package that decomposes and visualizes the electrical signals sent from our brains to various muscles.

Electromyography (EMG) is used to quantify the net electrical charge of a muscle as it contracts. In non-invasive electromyography, surface electrodes are placed on the skin and voltage is measured as participants flex and relax a muscle. The collected signal is the sum of all the electric action potentials fired from motor neurons attached to muscle fiber. A motor neuron, along with its connected muscle fibres, is known as a motor unit. Typically, researchers are interested in discovering when and which motor units contributed to the net EMG signal.

Currently, the Sensorimotor Physiology Lab at UBC School of Kinesiology decomposes EMG signals using a free software from OT Bioelettronica, which parses the individual action potential spike trains using a closed-source algorithm ("OT Bioelettronica - Home," n.d.). This type of decomposition is known as a convolutive blind source separation algorithm and is based off a paper published by Negro, et al (2016), which provides the mathematical logic and pseudocode used to build the algorithm (Negro et al. 2016). The algorithm employs high-level linear algebra and unsupervised learning techniques, such as Latent Component Analysis and K-Means classification.

The goal for this project is to recreate the blind-source separation algorithm described in Negro, et al (2016). Additionally, we hope to create a visualization tool that allows users to view the deconstructed EMG signals. To fit the needs of the Sensorimotor Physiology Lab, we will modify the program to deconstruct EMG recordings up to 5 minutes in length. Currently, the Bioelettronica software limits EMG decomposition to 100 second long recordings.

The final data product we will deliver is a Python package, emg-decomPy, that contains the decomposition algorithm and the visualization tool. We aim for emg-decomPy to be open-source and transparent, so future parties can customize or further develop functionalities. To accomplish this, there will be a large emphasis on documentation throughout the development of the package. While made for the Sensorimotor Physiology Lab, it is our hope that emg-decomPy will be a useful package to broadly explore the mechanisms underlying the brain's interactions with our muscles.

Data Science Techniques

There are two primary goals we identified within this project, and the techniques will be chosen based on those components. Our first goal is to build custom software that inputs the raw signals provided by the surface electrode and outputs the decomposed data. Our second goal is to visualize the decomposed signals.

We also have stretch goals contingent on completing the primary goals in time. The first stretch goal is to provide a GUI for manually marking false positives. This would include marking a false positive signal on the decomposed graph, and removing it from the visualization and the decomposed signal. At the same time, we will analyze whether the software can be optimized software based on the user's specific needs. To do so, we will review whether anything within algorithm can be hard-coded, skipped, vectorized, simplified or limited in a way that improves performance. If we still have time left in the project, we can begin to take steps towards the "interactive learning" upgrade. This would allow the user to mark false positive observations from a beginning sample of the decomposition, allowing the algorithm to take into account this new information in the rest of the decomposition.

Techniques and Tools in the original algorithm (Negro et al. 2016)

The primary tool described in the Negro et al paper that our software will utilize is the convolutive/iterative blind source separation algorithm for the decomposition of EMG signals. This algorithm, in turn, is based on the general decomposition framework and validation technique presented in earlier works, including (Holobar et al. 2010), (Marateb et al. 2011), and (Hu, Rymer, and Suresh 2014). The Convolutive blind source separation technique is a combination of latent component analysis (LCA) and iterative fixed-point K-means classification. LCA extracts meaningful features out of a large set of EMG signal observations to identify motor unit activity potential discharges, and K-Means performs classification into individual motor units.

Additional Techniques and Tools

Our project is primarily based on replicating the algorithm from the Negro et al paper, so at this point we do not plan to attempt any other techniques for decomposition. However, we may explore possible alternative techniques if we get to the optimization stretch goal. One possible technique to consider is RNNs or bi-directional RNNs since we are dealing with time series type data. We will also check if there were any advances in machine learning techniques since the release of this software to see if there are any useful novel techniques that haven't been considered at the time of writing this paper, such as transformer algorithms.

We will use a combination of tools for the development setup. We will use GitHub for collaborative version control of our package. We will develop Jupyter notebooks for small intermediate steps and as a sandbox to try out contained modules. Once the algorithm has been built, we will use a virtual machine by SageMaker lab, which will solve two problems. First, the existing black-box software is Windows-only, and using SageMaker VM will allow us to test our algorithm against the original. Additionally, SageMaker will provide us with the computational power to run longer sequences of motor unit action potentials (MUAPs). We will ultimately provide the solution in the python package, emg-decomPy. This package will be set up with cookie cutter and utilize poetry for dependency management and configuration.

Timeline

Dates in this timeline are tentative as we are still defining the scope of the project:

May 6, 2022: Present the proposal presentation to colleagues and project mentor.

May 10, 2022: Submit a draft written proposal to the project mentor.

May 12, 2022: Revise the report by incorporating feedback from project mentor (in some cases this may involve more than one round of revisions).

May 13, 2022: After receiving permission from the project mentor, submit the finalized proposal to the capstone partner and project mentor.

May 26, 2022: Complete replicating the original algorithm and present it to the partner.

June 1, 2022: Present visualization component to the partner.

June 5, 2022: Make revisions to the algorithm and visualization based on last meeting.

June 7, 2022: Propose changes to improve and optimize the original algorithm.

June 12, 2022: Implement proposed changes and optimizations.

June 14, 2022: Revisions to the original algorithm.

June 17, 2022: Final presentation.

June 22, 2022: Draft data product and draft final report.

June 29, 2022: Submit data product and final report.

References

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