Decomposition of Muscle Activity for Sensorimotor Neuroscience Proposal

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Executive Summary

Muscle movement is facilitated via the nervous system, which transports action potentials (electrical signals) from the brain to motor units. The motor units pass these electrical pulses through a motor neuron attached to muscle fibers, causing the muscle to contract (Purves 2018). 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 (Negro et al. 2016).

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. Currently, the blind source algorithm identifies individual motor unit action potential peaks and their firing times within an experimental duration limit of 100 seconds. Incorrectly identified peaks are then manually removed post hoc. Ideally, experiments of up to 5 minutes would be able to be processed by the algorithm. Instead of manually removing all false positives, 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 Sensorimotor Physiology Laboratory's use case. The second component is a non-interactive visualization element that allows users to view the decomposed output of the algorithm.

Introduction

Motor neurons are the junction between the central nervous system and the muscular system, enabling the muscular movement of daily life (Purves 2018). Degeneration of the motor neurons, through aging or neuromuscular disorders, therefore leads to difficulty in mobility and communication (Purves 2018). Thus, it is imperative to study motor neurons 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 central nervous system through motor neurons to various muscles.

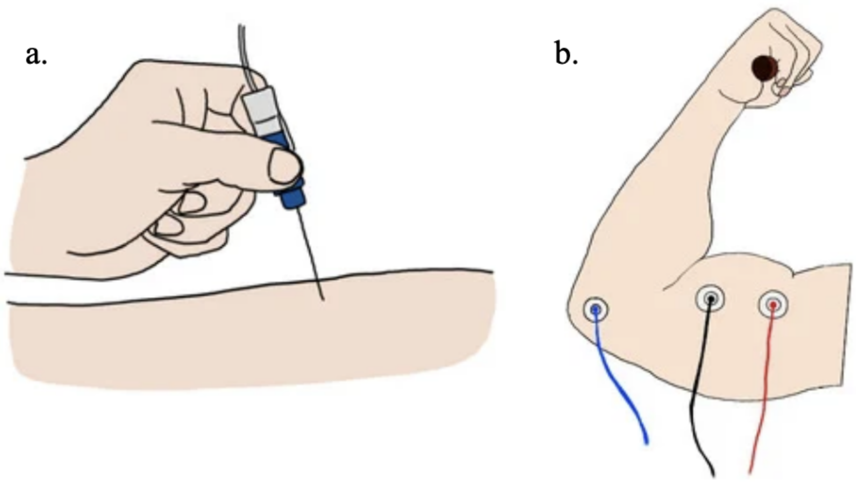

Figure 1: Obtaining electromyographs with a. surface electrodes and b. needle electrodes ("Electromyography: Encyclopedia Mdpi", n.d.).

Electromyography (EMG) is used to quantify the net electrical charge of a muscle as it contracts. Invasive electromyography involves the insertion of a needle electrode into the muscle, as pictured in **figure 1a**. Invasive electromyography is the more commonly used technique, as it allows for deeper muscle groups to be accessed, and the manipulation of the electrode to sample different parts of the muscle and to optimize the signal ("EMG Decomposition Tutorial" (n.d.)). In non-invasive electromyography, surface electrodes are placed on the skin, as pictured in **figure 1b**, and voltage is measured as participants flex and relax a muscle ("EMG Decomposition Tutorial" (n.d.)). This technique is the one that the capstone partner is interested in, and has advantages that include ease-of-use and more flexible applications. In addition, recent advances in technology and data science have increased the utility of non-invasive EMG, as raw EMG signals can now be decomposed into their constituent individual motor unit action potentials, whereas this was previously only feasible with invasive EMG [negro_muceli_castronovo_holobar_farina_2016].

The raw EMG signal is the sum of all the electric action potentials fired from motor neurons attached to muscle fibres (Negro et al. 2016). A motor neuron, along with its connected muscle fibres, is known as a motor unit (Purves 2018). Decomposing the raw EMG signal into the contributions of each individual motor unit, the process of which can be seen in **figure 2**, provides crucial information in research areas such as motor neuron discharge behaviour and muscle architecture, which deepen our understanding of the human body and can be used in diagnosing muscular disorders (McGill, Lateva, and Marateb 2005)("EMG Decomposition Tutorial," n.d.).

Currently, the Sensorimotor Physiology Laboratory decomposes EMG signals using a free software from OT Bioelettronica, the graphical user interface (GUI) of which can be seen in **figure 3**. This software determines the individual motor unit action potential spike trains using a closed-source algorithm. 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. 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). Primary steps of the algorithm are visually summarized in **figure 4**. The first three steps (I, II, III) are essentially data wrangling of the input signal, including extending of the channels and whitening of the resulting matrix. These data manipulation steps are followed by two fixed point algorithm iterations (IV

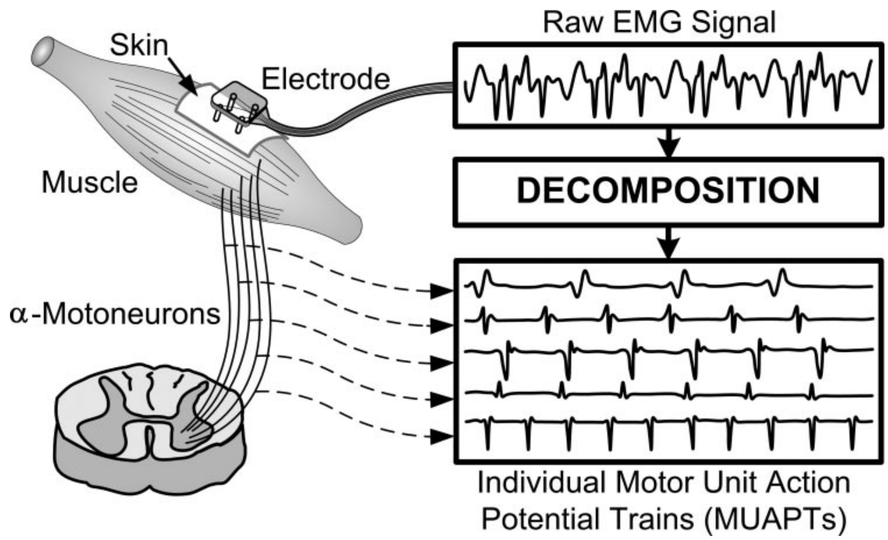

Figure 2: Decomposition of surface EMG signal into individual motor unit action potential spike trains (De Luca et al. (2006).

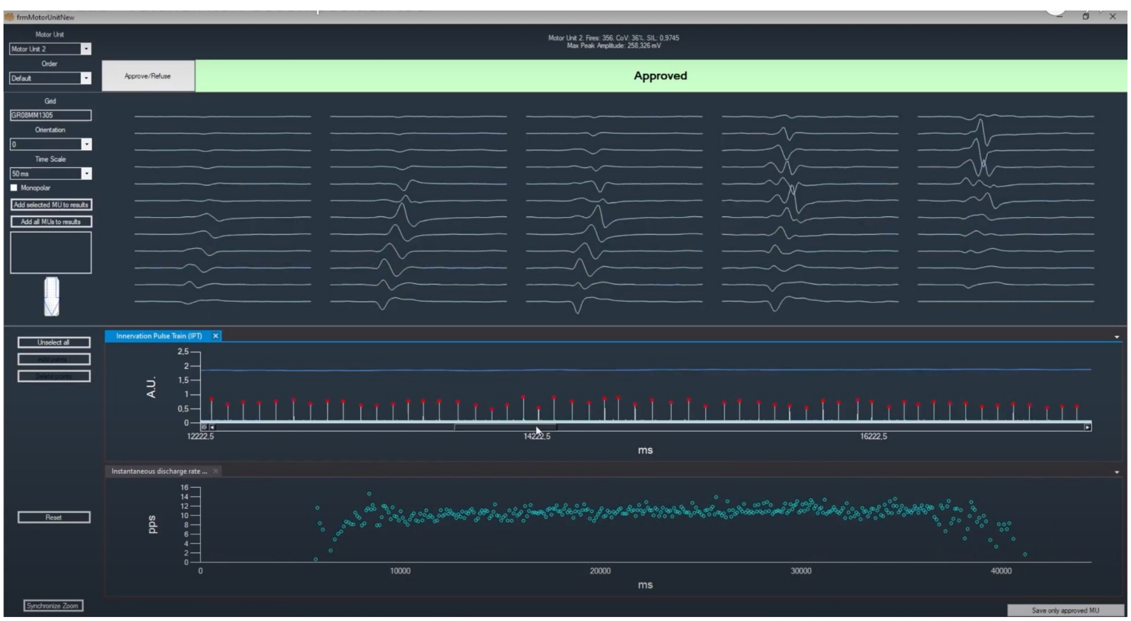

Figure 3: Graphical user interface of the OT Biolettronica software.

and V), which utilize machine learning for the optimal decomposition of the signal into individual motor unit action potentials. Step VI of the visualization displays the way that the quality of decomposition is estimated and improved at each iteration.

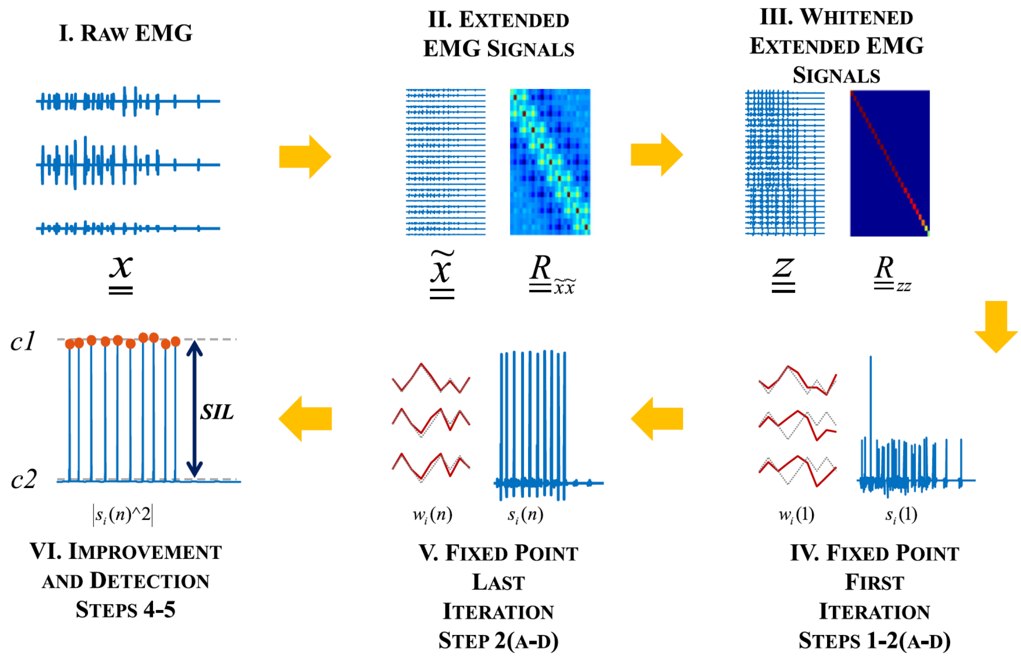

Figure 4: Visual step-by-step summary of the blind-source separation algorithm from Negro et al. (2016).

Additionally, we hope to create a simple non-interactive visualization tool that allows users to view the deconstructed EMG signals. To fit the needs of the Sensorimotor Physiology Laboratory, we will modify the program to decompose EMG recordings of up to 5 minutes in length. Presently, the OT Bioelettronica software limits EMG decomposition to 100 second long recordings.

The final data product is a Python package, `EMGdecomPy`, that contains the decomposition algorithm and the visualization tool. We aim for `EMGdecomPy` 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 Laboratory, it is our hope that `EMGdecomPy` 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. The techniques and tools in this proposal are based on these two components:

1. Build custom software that inputs the raw signals (see **figure 5**) provided by the surface electrode and outputs the decomposed data.
2. Create a tool to visualize the decomposed signals.

Stretch Goals

We have stretch goals contingent on completing the primary goals in time.

1. Provide a GUI in the visualization tool for manually marking false positives. False positives, in the context of the EMG data, are action potential peaks incorrectly identified by the decomposition algo-

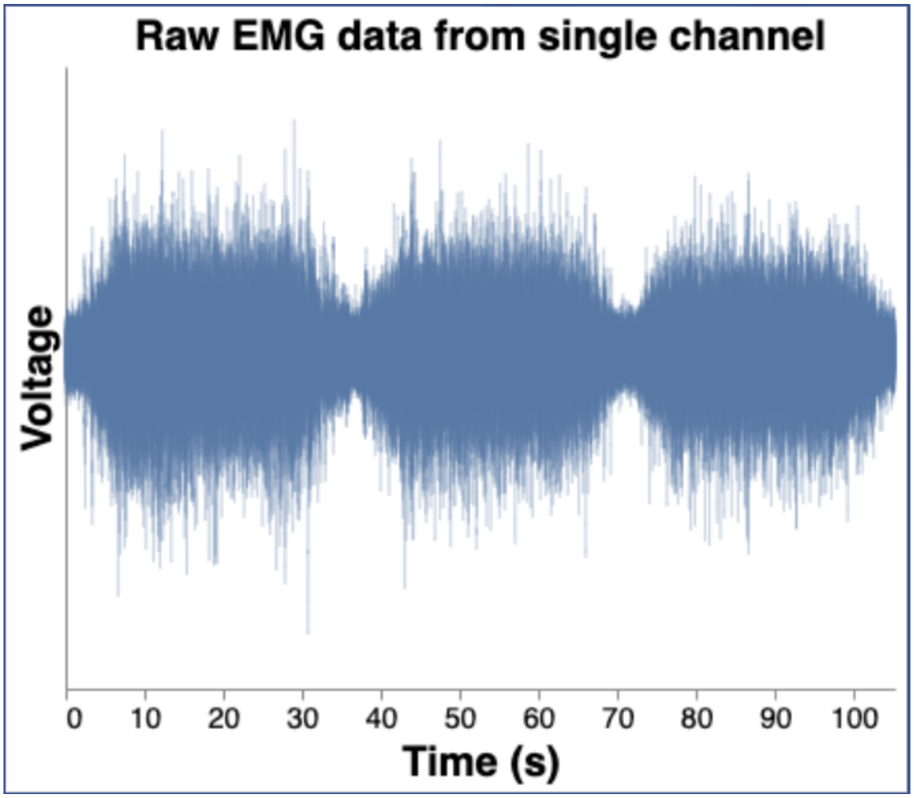

Figure 5: A raw EMG signal prior to decomposition. Data obtained from Negro et al. (2016).

rithm. The GUI would allow users to mark a false positive signal on the decomposed graph, removing it from the visualization and the decomposed data.

2. Analyze whether the software can be optimized based on the user's specific needs. As is, the decomposition algorithm is a robust, generalization solution that requires a lot of computational power. To cut down on computation time, we will see if any of the steps can be simplified, skipped, or reduced to better fit the specific needs of the Sensorimotor Physiology Laboratory.
3. If there is still time left in the project, we can begin to take steps towards the "interactive learning" upgrade. This would allow users to mark false positive observations from a sample of the beginning of the decomposition, allowing the algorithm to integrate this new information into the rest of the decomposition.

Techniques and Tools

The primary tool described in the Negro et al. (2016) 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 et al. (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.
- K-Means performs classification on individual motor units.

We will use a combination of tools for development.

- GitHub for collaborative version control of our package.
- Jupyter notebooks for developing minor, intermediate steps. Additionally, the notebooks can be used as a sandbox to try out contained modules.
- SageMaker Lab to build a virtual machine, which will solve two problems.
  1. The existing black-box software is Windows-only, and using SageMaker VM will allow us to test our algorithm against the original.
  2. SageMaker will provide us with the computational power to run longer sequences of motor unit action potentials.

We will ultimately provide our product in the python package, `EMGdecomPy`. To help us with the set-up and distribution of this package, we will use:

- `Cookiecutter`, package that sets up Python package boilerplate from a Python project template.
- `Poetry`, a tool for dependency management and packaging in Python.

Stretch Goals Techniques and Tools

Our project is primarily based on replicating the algorithm from the Negro et al. (2016) 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 are recurrent neural networks (RNNs) or bi-directional RNNs. RNNs are a type of neural network that retains "memory" between each learning step, making it a powerful tool for working with sequential data, such as time series.

Timeline

The proposal was created over the course of the first week of the capstone project. During the partner meeting on Thursday May 12, 2022, Jean-Sebastian introduced the team to the repository he discovered where another developer replicated the algorithm from Negro et al. (2016). The repository in question is not a python package but rather a simple set of functions without docstrings or testing mechanisms in place. Contingent on the response from the developer, the team will either build upon his existing code, or use it as an additional reference when writing functions for the steps of the algorithm. Regardless, the team agreed that this finding pushed the timeline up and made stretch goals more achievable. So while the primary objective remains to deliver an open-source python package replicating the algorithm, the tentative timeline has been sped up and now includes the stretch goals.

Note: 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 13, 2022: Submit the finalized proposal to the capstone partner.

May 20, 2022: Complete replicating the original algorithm and present it to the partner.

May 27, 2022: Present visualization component to the partner.

June 1, 2022: Make revisions to the algorithm and visualization based on last meeting.

June 3, 2022: Propose changes to improve and optimize the original algorithm.

June 5, 2022: Demo live update functionality.

June 10, 2022: Implement proposed changes and optimizations.

June 14, 2022: Final revisions to the original algorithm and new functionality.

June 17, 2022: Final presentation.

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

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