Blind Source Separation

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1 Research Problem Statement

This project addresses the challenge of Motor Unit Decomposition (MUD) in High-Density Electromyography (HDEMG) data, with the goal of identifying number of motor units (MUs) and their activation instances. MUD involves separation of motor unit action potentials (MUAPs) from a complex signal mixture recorded through multiple electrodes on skin surface during muscle contractions.

The project draws inspiration from blind source separation techniques and applies them to the context of neurophysiology. The electrical signals generated by motor neurons, responsible for muscle contractions, are recorded through an array of electrodes. The challenge is akin to the cocktail party problem, where multiple sound sources are mixed together; here, MUs act as sources, and HDEMG electrodes serve as observations.

The proposed approach involves preprocessing the HDEMG data to filter out noise using a combination of bandpass and notch filtering. This preprocessed data is used in component analysis algorithms to obtain the desired result.

2 Literature Research

1. Blind Source Separation Techniques: - Hyvärinen, A., & Oja, E. (2000). "Independent Component Analysis: A Tutorial Introduction." This foundational work introduces independent component analysis (ICA), a powerful technique for blind source separation. ICA is pivotal for extracting motor unit action potentials (MUAPs) from the complex signal mixtures inherent in HDEMG data. The review acknowledges the significance of ICA and explores its strengths and limitations in the context of motor unit decomposition.

2. Neuroscience and Neural Signal Processing: - Purves, D., Augustine, G. J., Fitzpatrick, D., et al. (2001). "Neuroscience. 2nd edition." The literature review places the foundational neuroscience knowledge provided by Purves et al. within the framework of motor unit decomposition. It critically analyzes the relevance of neural signal processing concepts to the challenges posed by HDEMG data, emphasizing the need for a nuanced understanding of neural mechanisms.

3. Recent Advances in Blind Source Separation: - Hyvärinen, A. (1999). "Fast and robust fixed-point algorithms for independent component analysis." The review critically examines recent advancements in blind source separation algorithms, focusing on their potential application to the challenges posed by HDEMG data. It discusses the implications of algorithmic efficiency and robustness for the proposed MUD approach.

4. Performance Measurement in Blind Audio Source Separation: This paper provides an overview of the state-of-the-art techniques and metrics used for assessing the performance of blind audio source separation algorithms. The paper delves into the evaluation criteria, such as source-to-interference

ratio (SIR), source-to-artifact ratio (SAR), and perceptual metrics, and discusses their strengths and limitations.

5. Multichannel Blind Source Separation Using Convolution Kernel Compensation -This paper leverages convolution kernel compensation to estimate and remove the convolutional effects introduced during the mixing, allowing for the recovery of the original source signals. This method is particularly valuable in applications like audio source separation, where it is difficult to precisely characterize the mixing process. It enables the extraction of individual source signals from their mixed counterparts, contributing to applications in speech processing, music, and other fields where source separation is crucial.

3 Method of Solving

One promising and standard method for solving the blind source seperation is using the statistical method ICA (Independent Component Analysis). There are different variants of ICA based on the domain of data at hand and the constraints on the independence, like FastICA, non-negative ICA, Frequential ICA, etc. We propose to first experiment with the standard ICA followed by diligent postprocessing of the Independent components. Based on the obtained results and the performance of the algorithm, we then leverage non-negative ICA as the EMG data would be rectified and have only positive values. An interesting experiment to do is the ICA in frequency domain, so we will experiment with frequential ICA as the last step and analyze the results.

4 Dataset Used

The dataset drive provided was used as the primary dataset for this project. The dataset contains HDEMG data from the Tibialis anterior muscle (close to shin). The data corresponds to participants holding a force level (steady force 1) and ramping up the force level (increasing force 1 and increasing force 2).

5 Evaluation metric

We plan to use regression metrics, RMSE (Root Mean Squared Error) and R-squared that measure the regression fit of the individual components. Since, the channels are time-series, we also choose correlation as metric. Apart from the statistical metrics, we will leverage source-to-interference ratio (SIR), source-to-artifact ratio (SAR), and perceptual metrics that measures the final component quality.

6 Timeline

16th Oct to 27th October - Researching the biological working of the motor neuron and dataset preprocessing.

27th October to November 3rd - Working on Standard ICA implemented on the preprocessed data and post processing of the independent components and model evaluation

4th November to 5th November - Working on the Midterm report and Compiling submissions.

Post Midterm Evaluation - Implement Non-negative ICA and evaluating the performance of the same. This step also includes comparison of the performance of the above two methods and drawing useful conclusions. The idea would be extended to Frequency domain ICA.

7 Division of Work

Manohar Sai Alapati - Preprocessing, Domain Analysis, Feature Engineering

Aneesh Atkuri - FastICA, post-processing, metric analysis

Abhinav Venkatadri - Non-negative ICA, post-processing, metric analysis

Hariharan Chithalamangalam Saravanan- Frequential ICA, post-processing, metric analysis

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