Blind Source Separation

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1 Introduction

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

This project helps us understand neuromuscular activity at different contexts and has many clinical applications. It will help determining the activity of individual motor units which will provide insights into neuromuscular function. This will also help researchers understand how motor neurons coordinate muscle contractions, the typical count of motor neurons that are active during a specific movement, and not to mention their firing patterns. Motor unit decomposition also has potential clinical implications. For instance, in neuromuscular disorders, the firing patterns of motor neurons might be altered. By analyzing HDEMG data, clinicians could potentially diagnose or monitor the progression of such disorders.

2 Related Work

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.

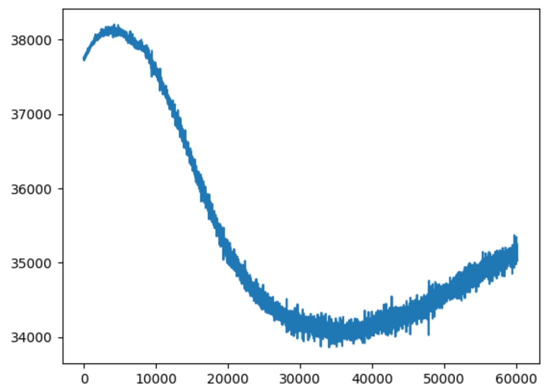
4. Performance Measurement in Blind Audio Source Separation: This paper provides an overview of the state-of-the-art techniques and metrics used for assessing the performance of blind audio source

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.

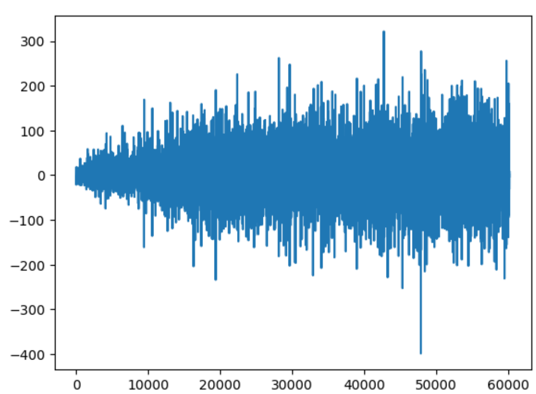
3 Dataset

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 observations corresponds to participants holding a force level (steady force 1) and ramping up the force level (increasing force 1 and increasing force 2). The following picture depicts the plot of channel 1 of Increasing force 1 dataset:



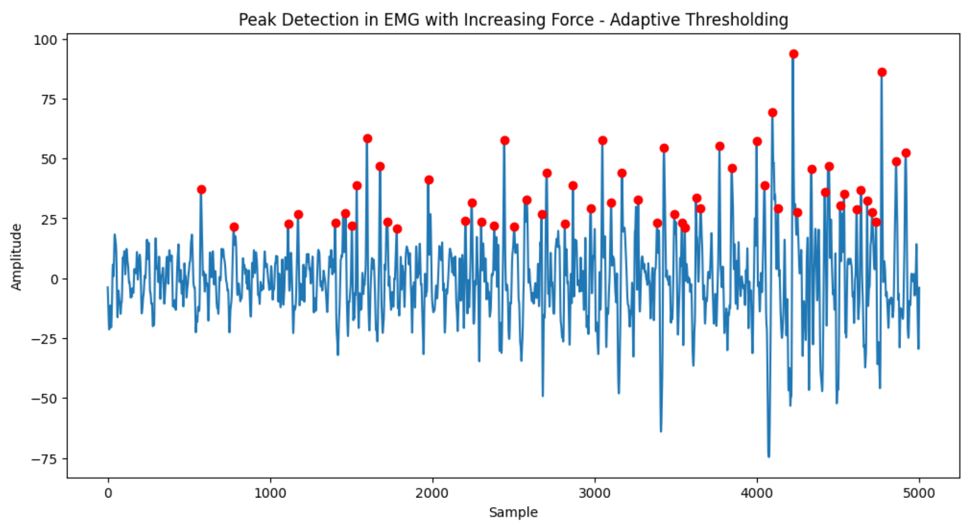
For an individual observation, the sampling rate is taken at 2048 Hz and contains action potential readings sampled across 64 channels that are uniformly placed in the hand.

Before extracting the individual MU's, it should be noted that the EMG signal is corrupted with noise. This includes collection noise and other interference from the MU's. So, we use a band pass filter by leveraging the fact that the EMG signal ranges from 20-500 Hz. This includes smoothening, band pass filtering and band stop filtering noise outside these frequencies. Specifically, we use a lowcut of 20 Hz, highcut of 500 Hz, f_s of 4000 Hz, order of 3, notch frequency of 50 Hz, notch quality of 30. The following picture depicts the filtered data on a channel 1:

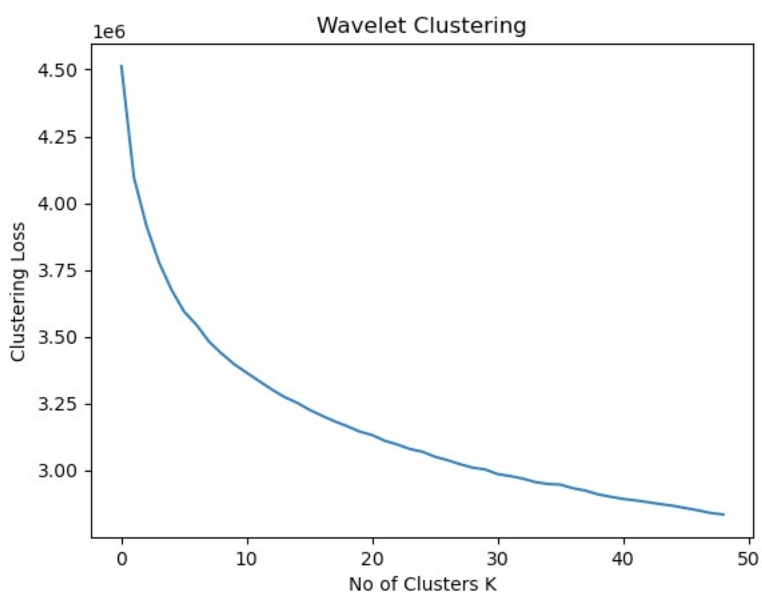


4 Results

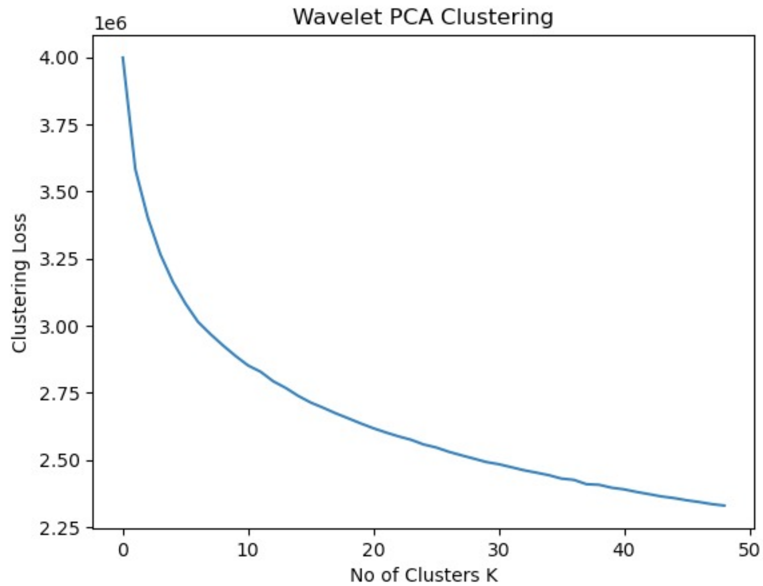
Peak detection: A peak duration of 60 ms and window length of 43 samples is considered. An adaptive thresolding method was considered for the task. The following plot depicts the number of peaks across the first channel for the increasing force 1 dataset for 5000 datapoints:



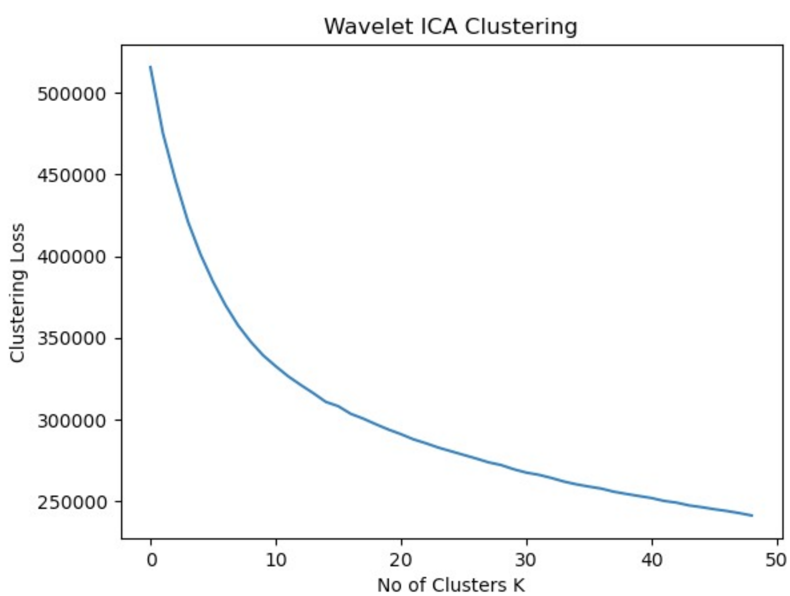
Wavelet followed by K-means++: The peaks were then passed onto wavelet transform and the wavelet components were analyzed and clustered. Based on the below plot, the number of clusters was observed to be 38 by custom elbow detection algorithm. The following plot depicts the clustering losses against number of clusters:



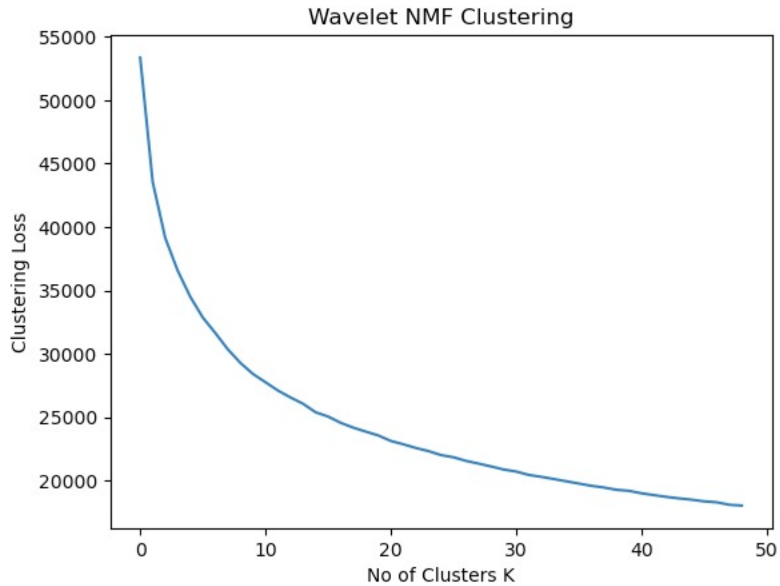
PCA followed by K-means++: The peaks were then passed onto wavelet transform and the principal componets were analyzed. The number of components was fixed based on the cummulative variance of around 95%. A total of 15 components were obtained. Based on the below plot, the number of clusters was observed to be 20 by custom elbow detection algorithm. The following plot depicts the clustering losses against number of clusters:



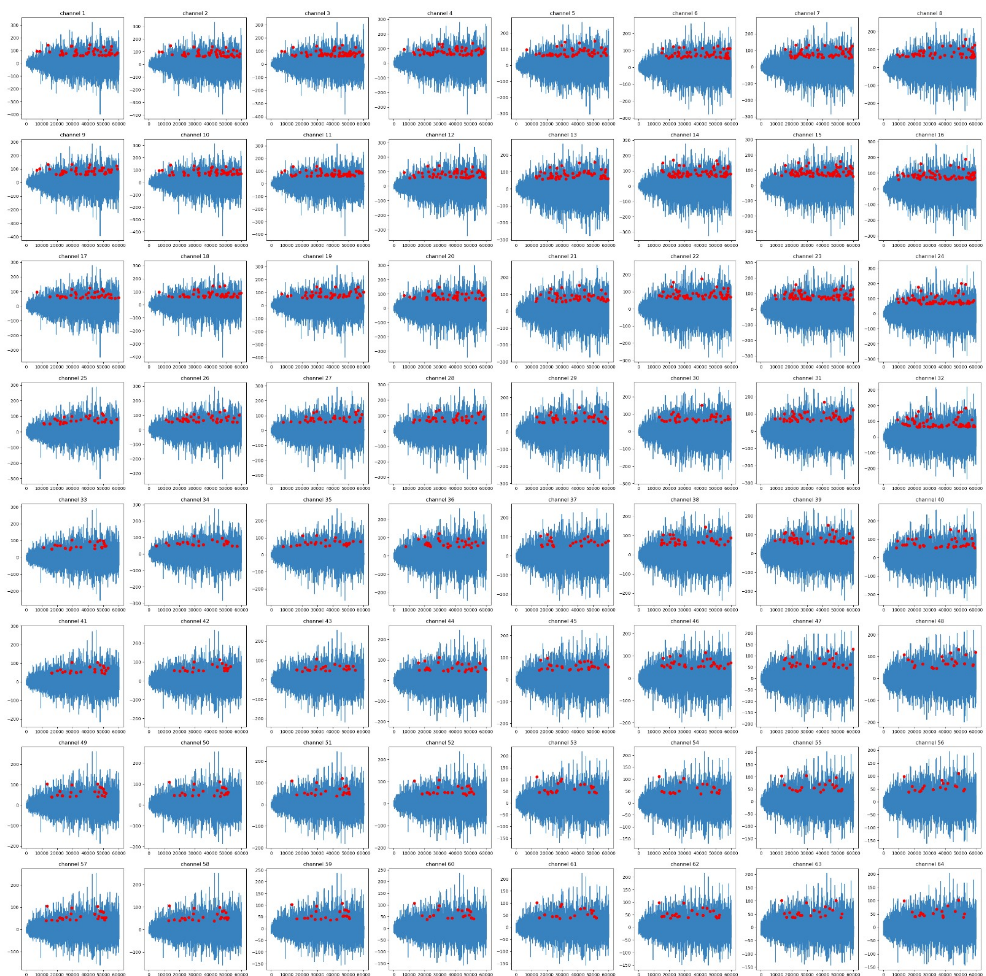
Fast ICA followed by K-means++: A total of 8 components were obtained. Based on the below plot, the number of clusters was observed to be 31 by custom elbow detection algorithm. The following plot depicts the clustering losses against number of clusters:



NMF followed by K-means++ : A total of 7 components were obtained. Based on the below plot, the number of clusters was observed to be 22 by custom elbow detection algorithm. The following plot depicts the clustering losses against number of clusters:



Unique MUs and firing instances : A total of 22 unique MUs are obtained based on NMF clustering plot. The firing instances are depicted for the 1st motor unit in the plot below:

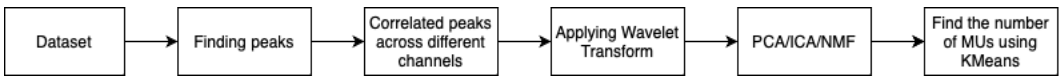


Based on qualitative evaluation, we find the peaks to be consistent with the interspike interval. The figure shows the proper correlation between the peaks of the given MU across the neighbourhood channels.

The Convolutional Kernel Compensation (CKC) method achieves the state of the art in decomposition. Compared to their approach, we use fundamental blocks to build and represent the signal. While the work evaluates their methodology using SNR on synthetic signals, we rely on simple qualitative approaches mentioned to check the base sanity of the decomposition due to the absence of a reference signal.

5 Methodology

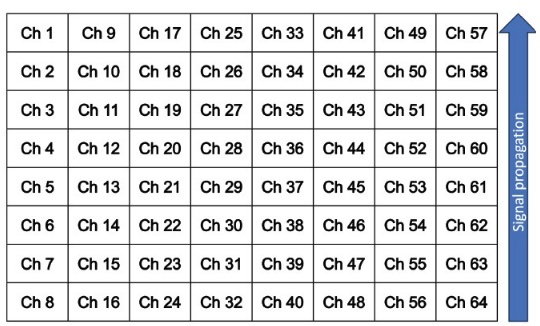
The block diagram of the algorithm flow is as follows:



Assumptions: Some assumptions and key takeaways from neuroscience are that, the Inter Spike Interval (ISI) for an MU is typically between 25 ms to 100 ms. Also, the peak duration is around 15-25 ms for a forcefully contracted muscle.

Peak detection : Based on the priors, we begin by applying a median filter to get an adaptive threshold for peak detection. This is consistent with the fact that the observations are given in the context of increasing muscle force. We then apply the peak detection algorithm with the given threshold and the distance between the peaks - configured based on the average ISI of an MU, to be 60 samples. The final peaks detected have false alarms for a few low hanging maxima. So, we take the mean of all the peaks across the signal and obtain the mean qualification for a peak. Consequently, we only retain peaks above this threshold. Inorder to obatin robust number of sources we combine the peaks detected from all 3 datasets and analyze the features.

Spatial feature capturing: In order to capture the feature correlation among different channels we compare and analyze the waveform of the peaks around a 3x3 grid around current channel of interest and average out the features to remove potential noise. Say we are considering peaks of channel 40 (refer the diagram below), we average out the peak information from channels 22:24, 30:32, 38:40, 46:48 and 54:56. This would help remove the correlations and prevent double counting of data points for component analysis and clustering.



Wavelet Transform and K-means++: For discrete wavelet transform, we have selected "db6" as presented in previous research. This is followed by K-means++ clustering method to negate the effect of initialization and obtain the clusters. From the clustering loss versus number of clusters plot above(in the Results section) and using custom elbow detection algorithm, total of 38 sources were obtained.

PCA and K-means++: Using the above obtained wavelet features, we find the principle components based on the cummulative variance of the components. A total of 15 components were considered with upto 95% variance and leaving out the remaining noise. This is followed by K-means++ clustering method to negate the effect of initialization and obtain the clusters. From the clustering loss versus number of clusters plot above(in the Results section) and using custom elbow detection algorithm, total of 20 sources were obtained.

Fast ICA and K-means++: Using the above obtained wavelet features, we find the independent components based on hyperparameter tuning. We consider Fast ICA to separate out the independent components of the MUs and identify the number of sources. A total of 8 components were considered . This is followed by K-means++ clustering method to negate the effect of initialization and obtain the clusters. From the clustering loss versus number of clusters plot above(in the Results section) and using custom elbow detection algorithm, total of 31 sources were obtained.

NMF and K-means++: Using the above obtained wavelet features, we find the semantically meaningful components using NMF. Inorder to make the data non-negative we shift the structure of the waveform up by the minimum most value. A total of 7 components were considered . This is followed by K-means++ clustering method to negate the effect of initialization and obtain the clusters. From the clustering loss versus number of clusters plot above(in the Results section) and using custom elbow detection algorithm, total of 22 sources were obtained.

Biological Plausibility: Based on the best obtained source separation method and clustering, we trace back to find the Inter spike interval of the obtained MUs and verify that they satisfy biological rules.

6 Discussion and Analysis

In the presented analysis, we examine the performance of three distinct dimensionality reduction techniques—Non-negative Matrix Factorization (NMF), Principal Component Analysis (PCA), and Independent Component Analysis (ICA)—applied within the context of K-means clustering. This examination is facilitated through the construction of a graph, plotting the loss (y-axis) against a varying number of clusters ranging from 1 to 50 (x-axis). Our findings indicate a notably superior performance of NMF in minimizing loss, in contrast to PCA and ICA. This enhanced efficacy can be largely attributed to the inherent characteristics of the data under study. Specifically, the correlation observed between sequential motor neuron activations presents a challenge to both PCA and ICA. These techniques, due to their underlying assumptions and operational mechanisms, are less adept at handling correlated data, resulting in a comparatively higher loss.

To address this, we have developed a custom method designed to identify the optimal number of clusters (K) for K-means clustering. This method employs the loss patterns elucidated from the application of NMF, PCA, and ICA, thereby providing a systematic and data-driven approach to determine the most effective clustering configuration. The optimal value of K is thus derived through a careful analysis of these patterns, ensuring an enhanced clustering accuracy and relevance to the neuronal activation data. There are a few methods to improve this analysis using attention based methods that can capture complex dependencies. One could also include temporal features to capture the correlations.

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