Second Assignment

Submission deadline: 30.01.2025 (by midnight)

1 Motor Unit Analysis

In physiology and neuroscience, the concept of motor unit decomposition plays a central role in understanding how our muscles work and how our nervous system controls movement. Motor units are the basic building blocks of muscle contraction. They consist of a motor neuron and the group of muscle fibers it innervates. This assignment is designed to introduce the basics of motor unit decomposition and provide insight into the principles of muscle function, neural control, and the technology used to study them.

For this assignment, we will work with a publicly available dataset that contains high-density surface EMG recordings from the lower leg muscles. The dataset can be accessed under the following link: https://doi.org/10.6084/m9.figshare.13695937. The corresponding publication with descriptions about the dataset can be found under this link.

For the motor unit decomposition, we use a slightly modified version of the open-source repository by Negro et al. (2016), which is accessible via the following link:
https://github.com/The-Motor-Unit/EMGdecomPy. For this exercise, please use the folder available on Moodle, which includes all the functions required for the decomposition.

1 Motor Unit Decomposition

- Download the folder Experimental_data_Raw.zip. Load the data from the file 'GM_10.mat'. Save the EMG signal (SIG), the force signal (ref_signal), and the sampling rate (fsamp) into separate variables.
- Concatenate all channels of the EMG signal vertically to create a two-dimensional array of size #channels * samples.
- Plot the first 10 channels of the EMG signal, displaying them below each other within a single plot. Label the x-axis in seconds to provide a time perspective.
- Decompose the EMG signal to extract firing instances of individual motor neurons (motor unit pulses). These instances represent the temporal firing patterns of motor units during muscle contraction. State the number of extracted motor units. For guidance on executing the decomposition process, refer to the documentation available in the provided repository above.
- Convert the motor unit pulses into binary spike trains. Ensure that the binary spike trains have the same length as the original EMG signal. Set the firing instances of motor units to 1 and all other values to 0.

- Visualize the firings of the first 4 motor units along and the force signal in vertically stacked subplots. Similar to the previous plots, label the x-axis with time in seconds.

2 Cumulative Spike Trains

Now we will compute the cumulative spike train of the motor unit firings. A cumulative spike train is a time-series representation of the cumulative number of spikes generated by a group of neurons. Instead of tracking individual spike events, it accumulates the total number of spikes that have occurred.

- Calculate the cumulative spike train (CST), which represents the cumulative number of spikes generated by motor units. Sum the binary codes for all motor units to create the CST. Create a plot of the CST with the x-axis labeled in seconds.
- Calculate the frequency of motor unit discharges (firings) using a sliding window approach with window sizes of 50 ms, 100 ms, and 200 ms. Shift the window forward by one sample at a time to maintain high temporal resolution.
- Plot the results for each window size to compare the effects of varying the window size. Reflect on how the choice of sliding window size influences the results. Discuss the implications of using smaller vs. larger windows in terms of temporal resolution, smoothing effects, and potential noise reduction. Consider what these findings reveal about neural activity patterns and the control mechanisms of motor units.

3 Spike Triggered Average

Spike-triggered averaging is a useful event detection tool that is often used in neural signal processing. The aim is to investigate the temporal relation between a spike train and a continuous EMG signal in order to reveal the response in electrophysiological activity preceding a spike.

- Compute the spike-triggered average for the first motor neuron for channel 50 using four different window sizes.
  - For each spike, compute a time window that is centered at the spike and holds values from -X to +X, with X being 15, 25, 50, and 100 milliseconds.
  - Compute the average of the extracted windows for each window size.
  - Plot the motor unit action potential waveform for the four different window sizes.
- Use a window size of 25 milliseconds and compute the spike-triggered average for each channel for motor neurons 21 and 41 (index 20 and 40). Plot the spike-triggered averages according to the electrode configuration. Please ensure that the subplots are added along the columns first. You should get a plot that looks similar to Figure 1. Figure 2 provides you with information about how the electrodes are arranged in the grid. Make sure the MUAPs are ordered accordingly.

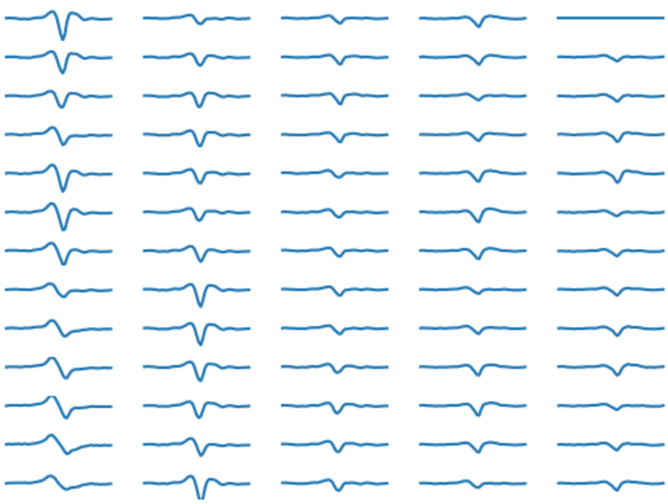

FIGURE 1 – Spike triggered average for 64 channels for one motor neuron.

FIGURE 2 – Example picture of the grids used in the experiment. The MUAPs in the plot above should be ordered according to the electrode number.

2 Muscle Synergies

The human body is a very complex and efficient system. The coordination of numerous muscles is required to perform even the simplest of movements, from lifting a cup of coffee to executing a perfect dance routine. Muscle synergies are a fundamental concept that helps us understand how the brain simplifies this complexity, allowing us to move with precision and ease.

In this section, we will explore the concept of muscle synergies, which are the coordinated patterns of muscle activation that the nervous system employs to execute various movements. By studying muscle synergies, we can gain deeper insights into how the brain controls and optimizes our actions.

For this task, we will use again the publicly available Hyser dataset that contains sEMG recordings from the arm for using four high-density surface EMG grids. The dataset can be accessed under the following link: https://www.physionet.org/content/hd-semg/1.0.0/. The corresponding publication with descriptions about the dataset can be found under this link.

1 Basic Concept of Muscle Synergies

- From the folder "pr_dataset", load from the first session of the first participant the EMG signal of "dynamic_preprocess_sample60" and "dynamic_preprocess_sample66" which contains the recording of pronation and supination.
- Concatenate the two signals together along the time axis and plot the first channel of the EMG signal.
- To identify noisy channels, compute each channel's Root Mean Square (RMS) value and plot the RMS values in a barplot. Identify and state the channels with an RMS > 0.2 and delete them from the signal matrix.
- Rectify the EMG signal
- Use Principle Component Analysis (PCA) to extract four components from the EMG signal. Plot the extracted components in four subplots. Use the extracted components to reconstruct the original signal. Compute and state the coefficient of determination R^2 for the reconstruction accuracy (the function np.corrcoef may help you). Plot the original and the reconstructed signal for the first channel for 500 samples in one plot and label the graphs accordingly.
- Perform the same steps as in the previous task, but this time, apply non-negative matrix (NMF) factorization for the extraction of synergies. Plot the elements of the W (weights of respective channels - should be visualized as a barplot) and H (continuous signal) matrix. State R^2 for the reconstruction accuracy.
- Discuss the differences between the two methods.

2 Selection of Synergy Number

- Use NMF to extract 1 up to 15 components. Compute the coefficient of determination R^2 for each iteration.
- Plot the values for R^2 and label both axes correctly. Plot the original EMG signal and the reconstructed signal for the first channel for 500 samples using 1, 3, and 15 factors.
- Your reconstruction accuracy should be at least 0.85. Select the appropriate number of components based on this condition and state the number of chosen factors.

3 Submission

- Submission of the code and report (in pdf) in one .zip folder uploaded in Moodle.
- Your folder should be named with NAME_SURNAME_EX2.

We wish you good luck and hope you enjoy the exercise!