ECE-374N/385J

Neural Engineering - Spring 2022

ECE Department, The University of Texas at Austin

HW-II
Analysis of Electromyography (EMG) Signals

Out: Wednesday, February 15, 2023 *Due: Wednesday, March 8, 2023*

*Note-1: Please start early! We will hold a QA session next Wednesday in which you can ask questions *after* you have started on your HW and tried as many questions as possible.*

Note-2: Group discussions with your classmates are encouraged, but you have to submit your own individual work! Make sure to analyze the results you report and to suggest ways of improvement to the applied methods!

1 Overview

In this HW, you will analyze electromyography (EMG) signals recorded through surface electrodes placed over the muscles of the forearm. Non-invasive EMG measures the collective electrical activity of a muscle in response to a nerve's stimulation of that muscle. You will analyze EMG signals recorded from the proximal and distal parts of the Flexor Carpi Radialis and the Extensor Digitorum muscles of the forearm (shown in Fig. 1) while subjects perform three different hand movements shown in Fig. 2:

Grasp: Flexing the fingers

Pinch: Fine pinching using the thumb and the index and middle fingers

Point: Pointing forward with the index finger

The objective of this HW is to characterize EMG activity in the four locations of the forearm for each of the performed hand movements, and then to try to classify the type of movement using EMG signals.

Recommendation: Look into the literature on EMG analysis and EMG-based classification of hand movements!

1.1 Data Description

Six runs of EMG recordings were completed by two subjects. A run consists of 10 trials of each of the three movements. Trials start with a rest period of 1-1.5s followed by fixation for 1s, cue presentation

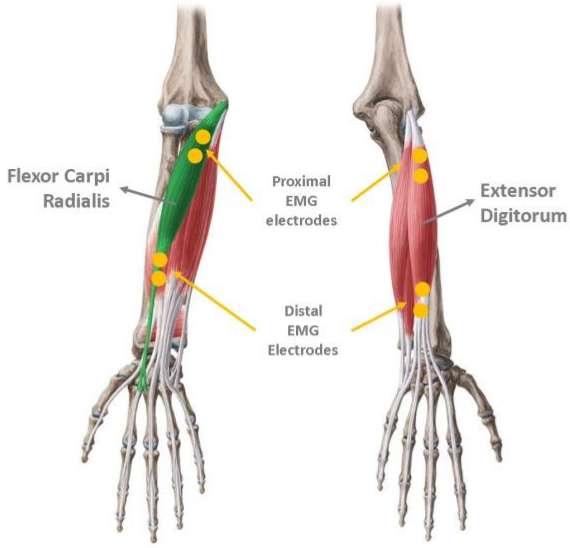

Figure 1: Positioning of EMG electrodes on the forearm.

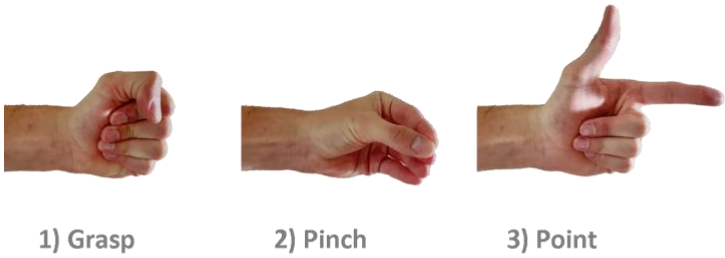

Figure 2: Illustration of the performed movements.

for 2s, task execution for 2.5s, and feedback on the end of trial for 1s. In all of the recordings, EMG signals were recorded from the four location on the extensor and flexor muscles.

You will be provided with a data file that contains the following for each subject:

subject.run(i).emg: (#*samples* × #*sensors*) contains emg data of *run-i*

subject.run(i).header: contains the header of *run-i*

- subject.run(i).header.fs: sampling rate
- subject.run(i).header.Label: labels of the 4 EMG sensors in the order as in the data matrix
- subject.run(i).header.EVENT.TYP: triggers marking the events of a trial
- subject.run(i).header.EVENT.POS: position in samples of each of the logged triggers

Table 1 and Fig. 3 below detail the description of the triggers:

Table 1: Summary of the in-lab recorded meditation dataset.

Trigger	EVENT.TYP	Description
Run Start/End	32766	marks the start and end of a run
Trial Start	1000	Start of a new trial - beginning of inter-trial rest period of 1-1.5s
Fixation	768	Fixation Cue presented for 1s
Task Cue	100/200/300	Task cue presented for 2s in Pinch, Point, and Grasp tasks respectively
Task Start	101/201/301	Task execution starts in Pinch, Point, and Grasp tasks respectively
Task End	102/202/302	Task execution ends in Pinch, Point, and Grasp tasks respectively after 2.5s

Figure 3: Triggers in a single trial.

2 Tasks

2.1 Preparing the Signals

1. Extract the first trial in run-1 of subject-1's data: plot the time series signal over time (in seconds) for the 4 EMG sensors and add labels for the trigger locations. What kind of movement was performed in that trial?

2. From the above trial, extract the rest and task periods recorded over the distal flexor muscle and plot their PSDs in one figure. What band characterizes the electrical activity due to the activation of the muscle?

3. Filter the data of all runs and all subjects to the appropriate frequency band for EMG analysis. Perform other necessary filtering if your band contains a potential source of interference!

4. After filtering the data of the two subjects, extract the task periods of all trials in all runs and keep track of their corresponding class (Grasp, Pinch, or Point). A convenient way of storing this data for each subject is a variable of dimensions ($\#trials \times \#sensors \times \#samples_{task}$) to store the data and a vector of dimension ($\#trials \times 1$) to store the classes.

2.2 Feature Extraction: use filtered signals

1. Implement the MAV feature from the last HW along with at least one other feature of your choice after looking at the literature on EMG-based classification of hand movements. Decide on the window size and percentage of overlap for computing the features. Your choice shall allow for proper computation of the features and for real-time classification.

2. For each of the two subjects, compute the features of the three classes over all runs and for all four EMG sensors.

3. For each of the sensors, scatter plot the feature samples of the three classes in a 2D feature space. (Note: use different colors for different classes and show results for each subject). Comment on the figures.

2.3 Average Patterns

A major challenge when dealing with physiological signals lies in separating the signal of interest from noise. An approach to do so and increase the signal-to-noise ratio is by averaging across multiple trials to get a mean signal. This is only valid as long as the signal of interest is similar in each of the trials. The noise, on the other hand, will vary across trials.

Denote by $x_i[n]$ the noisy signal for each specific movement trial i. x_i has the signal of interest $s[n]$ due to muscle activation and an unwanted noise component $d_i[n]$. $s[n]$ is assumed to be approximately the same for the same movement across trials.

$$x_i[n] = s[n] + d_i[n] \tag{1}$$

Now, assuming that $d_i[n]$ is zero mean white noise ($< d_i[n] >_i = 0$, averaging across i), then:

$$\mu_x[n] =< x_i[n] >_i =< s[n] >_i + < d_i[n] >_i = s[n] + 0 = s[n] \tag{2}$$

Accordingly, to retrieve $s[n]$ from the noisy signals $x_i[n]$, we need to average across many trials.

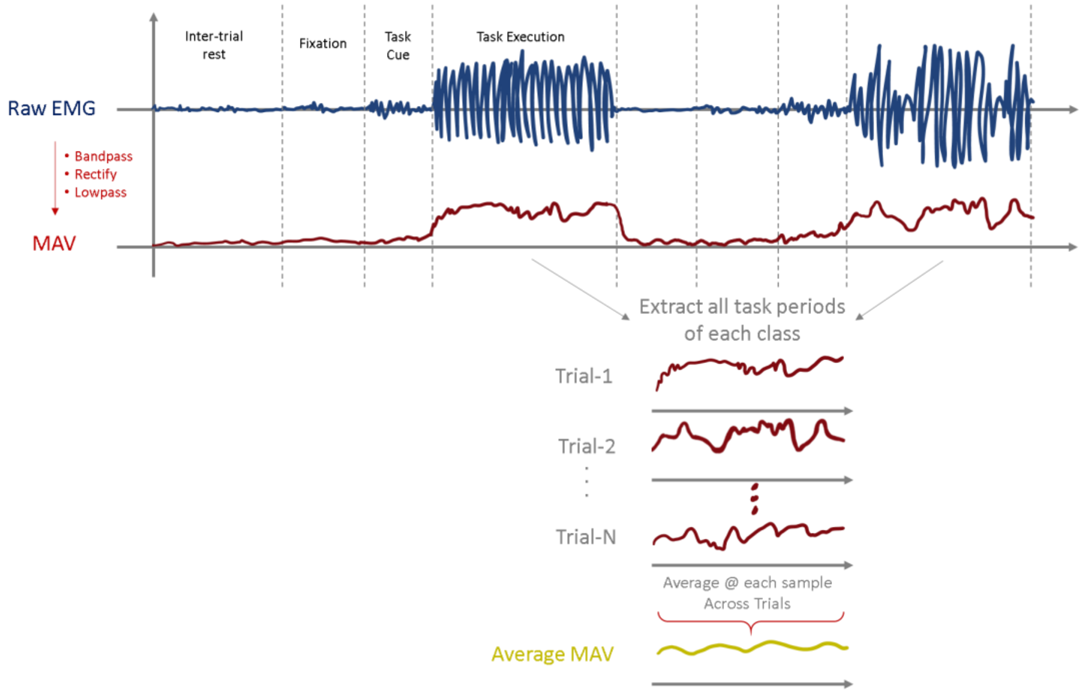

Figure 4: Illustration of trial averaging.

Average MAV pattern: We will only use the EMG signals recorded from the proximal flexor muscle of Subject-1 in this exercise.

1. Figure 4 illustrates how to get the average MAV pattern for each movement class. Start with the raw data of the subject, filter it to the same range you used in Exercise 2.1-3, take the absolute value, and lowpass filter the result with a cut-off frequency of 5 Hz. (Note: lowpass filtering is equivalent to temporal averaging). Now we have the MAV values over the trials. For each sample during the task period, average the MAV value across trials in order to obtain the corresponding MAV pattern. Do it for each movement separately.

2. Plot the MAV patterns of 5 random trials along with the average MAV. You should report a figure for each type of movement. Comment on the results.

3. How do the average patterns of this exercise compare with the distributions of MAV features in Exercise 2.2-3. Comment on the results.

2.4 Classification

1. Use both features to build a 3-class classifier for each subject. Use only the first 5 runs to optimize the choice of the classifier through run-wise cross-validation (Experiment with at least two classifiers: e.g. linear and quadratic LDA). What is the advantage of using run-wise cross validation?

2. Test your chosen per-subject classifiers on the corresponding sixth run of each subject. How does the classification accuracy compare with the run-wise cross-validation accuracy? Comment on the result.

3. **Transfer Decoders**: Test the decoder of each subject on the sixth run of the other subject. Comment on the results.