SYDE 544: Biomedical Measurement and Signal Processing

Assignment 4: EMG

Instructor: Steven Pretty

Due Date: Wednesday, March 22nd, 2023 (11:59 PM, EST)

Instructions: Your submission will include Part 1 (mandatory) and one of Part 2 or Part 3 (individual preference based on interest/computing resources). **It is not necessary to complete both Part 2 and Part 3**. If you chose to submit both Part 2 and Part 3 the best mark of the two will be utilized to calculate your assignment grade.

Part 1: Simulating EMG and Force Generation

In the folder you will find a data file (Ass4Part1_data) and skeleton script (Ass4Part1_script) to be completed (please do not modify variable names). You should submit the completed processing script and a pdf file with your generated figures and observations. Specific instructions and questions can be found below.

Part 2: Classify Arm Motions Using EMG Signals and Deep Learning (Option 1)

This option is intended to provide an introduction to EMG signal classification in MATLAB and does not require any individual coding or analyses. This example utilizes the parallel processing toolbox and will require substantial computation time. If you prefer not to utilize the parallel processing toolbox (it may require some configuration) set "UseParallel" to 'false' when calling 'readall'. Otherwise, simply work through the following MathWorks example:

https://www.mathworks.com/help/signal/ug/classify-arm-motions-using-emg-signals-and-deep-learning.html

Submit figures of your network training progress and confusion chart in pdf format (5 points)

Part 3: EMG Normalization (Option 2)

This option will provide insight into basic EMG processing relevant to determining a muscle's activation state. In the folder you will find a data file (emg) containing 'Raw' EMG from the biceps of two participants. You should submit a completed processing script and a pdf file with your generated figures and observations. Specific instructions and questions can be found below.

Part 1: Simulating EMG and Force Generation (15 points)

In this simulation, we consider the investigation of a motor unit pool with an unknown number of MUs. However, for surface recordings, we don't usually have access to the activities of all the MUs in the pool. Rather, we assume we have access to 120 superficial MUs. Since there is no spatial organization order with respect to the recruitment thresholds of these units, it is reasonable to assume these 120 MUs are representative to the physiological recruitment order: smaller units are recruited first (at lower threshold), larger units are recruited at higher threshold. Note that the size here refers to the size of the axon of the motoneuron and the size of force twitch generated by the MU, not the size of the action potential detected at skin surface. This is because a deep unit (very small action potential at surface) could be a large unit with large force output. Conversely, a superficial unit (very large action potential at surface) could be a smaller unit with small force output. Let's define the recruitment threshold of the *i*th MU as:

$$\mathrm{RTE}_i = e^{ai} \qquad (1)$$

where the constant a is:

$$a = \frac{\ln(RR)}{120} \qquad (2)$$

where *RR* is the largest recruitment threshold of MU pool (the recruitment of the largest unit). This means once the neural drive applying to the MU pool is larger than RTE_i, then the i*th* MU will be recruited, and start firing. With this simplified, yet rather realistic modelling, we can establish the ordered recruitment sequence of the MU pool: a majority of the MUs have small recruitment thresholds, and a small number of MUs have a high threshold. It is physiologically reasonable to have a 30-fold difference between the highest threshold and the smallest threshold. Therefore, we can set *RR*=30 (arbitrary unit) in Eqn. (2).

Once the *i*th MU is recruited at its recruitment threshold, RTE_i, it would fire at its minimal firing rate. And, as the neuronal drives increases, all MUs would increase their firing rates. A simple but realistic model for this behavior (rate coding) is:

$$\lambda_i = g_i(E - \mathrm{RTE}_i) + 8 \qquad (3)$$

where λ_i is the firing rate of the *i*th MU in response to the applied neural drive to the MU pool (*E*), which is common for all MUs. The coefficient g_i is a gain factor for the *i*th MU, and 8 (Hz) is the minimal firing rate (at the recruitment threshold), which is assumed to be identical for all units. To further simplify our simulation, let's further assume the maximal firing rate of all units to be 35 Hz, and the maximal neural drive is 36 (1.2 times larger than the maximal recruitment threshold). As such, the gain factor can be found by:

$$g_i = \frac{35 - 8}{1.2 - \mathrm{RTE}_i} \qquad (4)$$

Problem 1a: Obtain and plot the RTE_i for each of the 120 MUs (complete the code at Line 10-22 of the script) (1.5 points).

Problem 1b: Obtain and plot the g_i for each of the 120 MUs (complete the code at Line 25-35) (1.5 points).

Problem 2: Using RTE_i and g_i in Problem 1, generate a realization of the firing timings of all 120 MUs over approximately 10s, at each of the neural drive levels:

$$E = [3, 6, 9, 12, 15, 18, 21, 24, 27]$$

When generating the firing timings, the mean firing rate λ_i should be obtained from Eqn (3), the inter-firing interval should be modelled as a Gaussian variable with mean of $1/\lambda_i$ and coefficient of variation of 15%. Include a plot of mean firing rate for each MU at *E* = 27 (complete the code at Lines 38-55) (2 points).

Problem 3: In the provided data file, you can find a variable named, *MUAPs*. It contains the MUAPs of the 120 MUs (each column for a MUAP). The sampling rate is 4096 sample per second. Plot the 120 MUAPs on a single graph, you should see that there is no relationship between the size of the MUAP and MU id, as explained earlier (2 points). Using the firing timings generated in Problem 2, simulate the MUAP trains of all the units at the 9 levels of neural drive. Add the MUAP trains together, you would obtain simulated EMG signals at these 9 levels of neural drive. Plot the simulated EMG on separate subplots for each level of *E* (complete the code at Line 57-95) (3 points).

Problem 4: In the provided data file, you can also find another variable named, *F*. It contains the force twitches of the 120 MUs (each column for a MUAP). For each MU, a firing will generate one force twitch. The sampling rate is also 4096 sample per second. Plot the force twitches for each MU on a single plot, you should see that the force twitches are nicely ordered: the twitch of the first unit is the smallest and twitch of the last unit is the largest (2 points). Using the firing timings generated in Problem 2, simulate the force output of all the 120 MUs, at the 9 levels of neural drive. The summation of the force output of all units is the overall force output. Plot the simulated force output on separate subplots for each level of *E* (complete the code in Lines 98-128) (3 points).

Part 2: Classify Arm Motions Using EMG Signals and Deep Learning (5 points)

Simply work through the following MathWorks example:

https://www.mathworks.com/help/signal/ug/classify-arm-motions-using-emg-signals-and-deep-learning.html

Problem 1: Submit figures of your network training progress and confusion chart in a pdf file (examples below). Comment on your results (5 points).

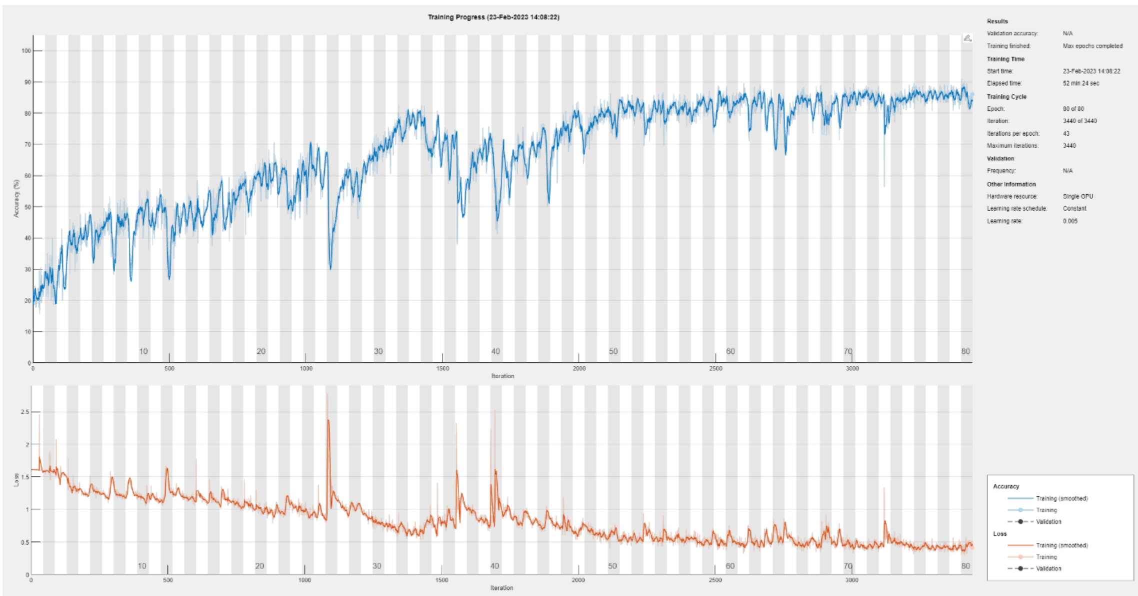

Figure 1: Network Training

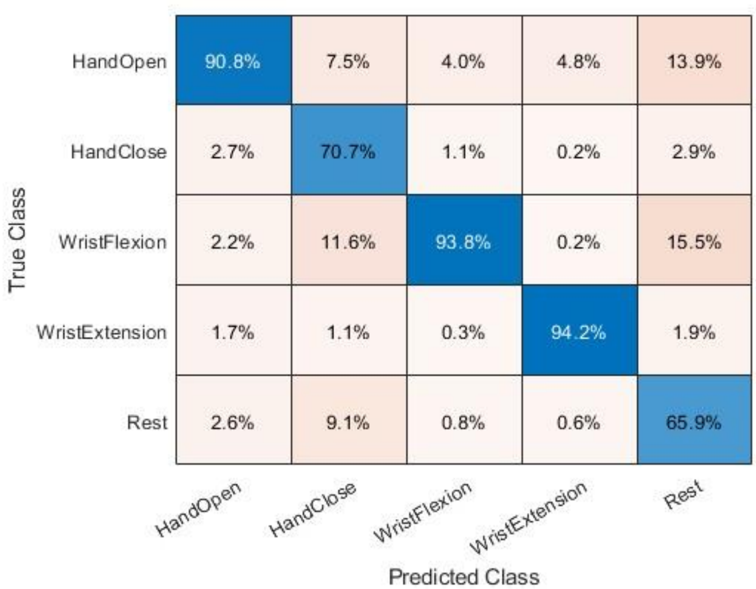

Figure 2: Confusion Chart

Part 3: EMG Normalization (5 points)

In the folder you will find a data file (emg) containing biceps EMG from two subjects. All trials were sampled at 3000 Hz and are organized in columns:

Column 1: Participant 1 - maximum voluntary contraction

Column 2: Participant 1 - chin-up trial

Column 3: Participant 2 - maximum voluntary contraction

Column 4: Participant 2 - chin-up trial

As discussed in lecture, a common processing approach is to full wave rectify and low pass filter the 'raw' EMG signal to generate linear envelopes. Perform this approach for each of the trials utilizing a single pass 4^{th} order Butterworth filter with an effective frequency cutoff of 5 Hz. In order to compare activation states across muscles, sessions, and individuals it is common to express linear enveloped EMG data with respect to a maximum voluntary contraction (MVC) for the muscle. Utilize the peak amplitude of each participant's linear enveloped MVC trial, to normalize their chin up trial (express as percentage peak MVC).

Problem 1: Generate raw and normalized linear enveloped EMG plots of the chin-up trial for each participant. Comment on your ability to compare participant data utilizing the raw compared to processed EMG data. What can and cannot be inferred from each plot/what do the plots represent (5 points).