# BME445 NEURAL BIOELECTRICITY
# Lab 1: INTRODUCTION TO BIORADIO AND SIGNAL PROCESSING
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**Purpose**

The purpose of this lab is to get familiarized with the BioRadio Software by investigating the effects of noise, sampling rate, and quantization parameters, as well as to review simple signal processing techniques. We will also observe how our muscle contractions affect the electromyogram (EMG), and how we can control a virtual robotic arm by separating physiological data from interference in the EMG, through spectral analysis, normalization, and filtering.

**Results/Discussion**

PART 1: Introduction to Data Acquisition and the Lab Course Software

***1. What is the signal generated from the Test Pack? Describe it in terms of its wave-shape, frequency and amplitude.***

As seen in *Figure 1*, the signal generated from the Test Pack is a square wave with a frequency of 10Hz (i.e. 10 cycles in one second) and approximately an amplitude of 150 μV.

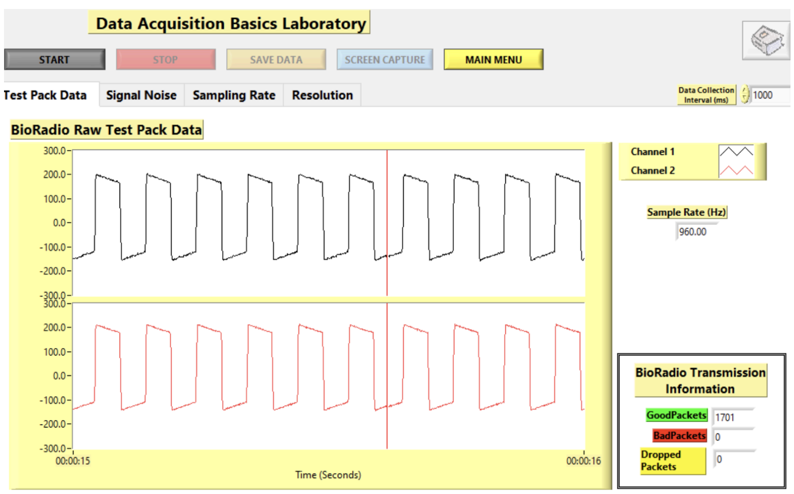


*Figure 1: Signal generated from the Test Pack*

***2. What is the largest physical distance the transmitter/receiver pair can tolerate before performance is affected?***

The largest physical distance our transmitter/receiver pair could tolerate was found to be 24.89 meters. To find this distance, we experimented in a hallway with no obstacles, such as walls. We identified this distance when we observed an increase in the number of dropped packets, indicating the boundary of the receiver's effective range.

***3. Investigate large and small data collection intervals. List the Pros and Cons for using a large data collection interval (before buffer overflows).***

We observed that the software was able to receive data at a relatively high interval compared to 1000ms, without the buffer overflowing.

With the interest of time, our team tested intervals up to 90000ms, and yet no “Dropped Packets” were observed.

Pros:

- Based on the documentation, in theory, with a larger data collection interval, data would be received less frequently.
- Larger intervals can help average out noise or fluctuations in the signal, making it easier to discern underlying trends and patterns in the data.

Cons:

- High-frequency components of the signal transmitted may be attenuated/lost when using a large data collection interval, potentially impacting the accuracy of signal analysis, especially for physiological signals with fast changes
- With longer intervals, it may take more time to detect and respond to problems or anomalies in the data collection process, since the data is received less frequently. This can be a drawback if real-time monitoring and immediate action are essential.

***4. Why should each transmitter/receiver pair use a unique carrier frequency?***

Each transmitter/receiver pair uses a unique carrier frequency as a means to minimize interference from other sources and to provide signal isolation, allowing each transmitter/receiver pair to transmit and receive data independently without affecting and being affected from other pairs.

***5. For input ranging from ±61mV using 16 bits per sample, what is the range of values represented by each bit?***

For low-level inputs, ranging from ±61mV using 16 bits per sample, each bit represents 1.86 μV.

$122mV/2^{16} = 1.86\,\mu V$

***6. Assume you are going to use the BioRadio to record two channels for 30-minutes with the BioRadio configuration given in the lab procedure. How many bytes would you expect that file to be if there are 12 bits/sample?***

We know:

- Sampling rate: 960Hz (960 samples per second per channel)
- 30 minutes = 1800 seconds
- 2 channels
- 12 bits/sample

The file size is expected to be:
2 channels * 12 bits/sample * (960 samples/second)/channel * 1800 seconds = 41472000 bits = 5184000 bytes = 5.18 MB

***7. What is the characteristic of a uniform white noise?***

White noise has zero mean, constant variance, and is uncorrelated in time. It is uniformly spread across all allowable frequencies. Uniform White Noise with the amplitude of 25μV plotted over the Test Pack Signal can be seen in *Figure 2*.

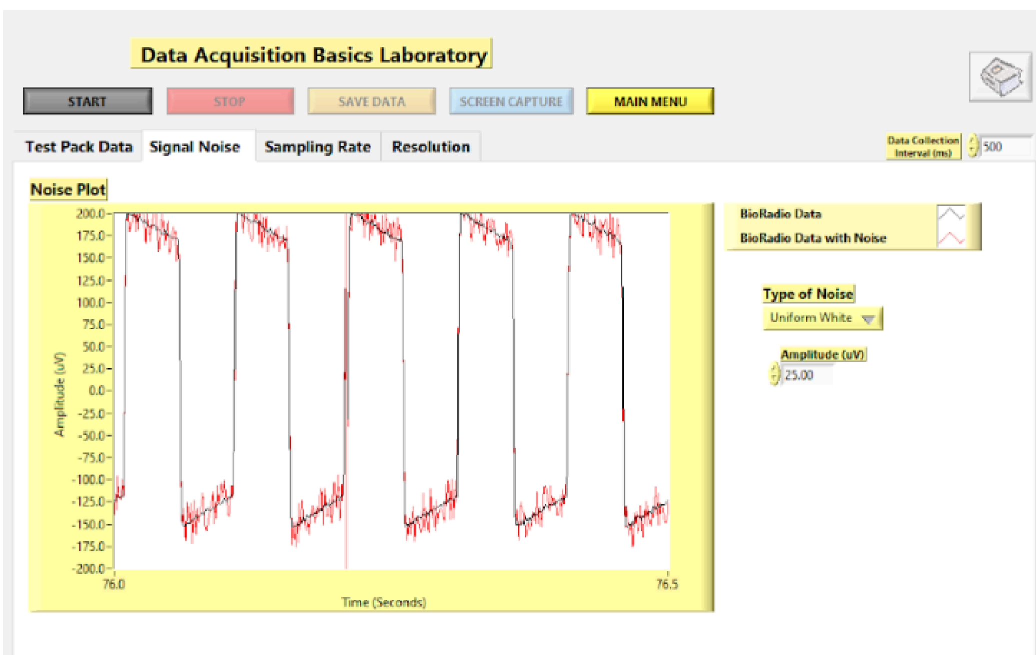


*Figure 2: Test Pack Signal with Uniform White Noise with an amplitude of 25 μV*

***8. What sources of noise would you expect when recording EMG, EEG, and EOG signals besides 60 Hz from power sources?***

Other sources of noise that you expect when recording EMG, EEG, and EOG signals besides 60 Hz from power sources include:

- Biopotentials from other parts of the body that are not intended for measurement. For example, activity from neighboring muscles or involuntary muscle movements can contaminate the signal.
- Electromagnetic Interference (EMI) and Radio Frequency Interference (RFI) caused by external sources such as phones or other lab equipment and devices.
- Poor electrode-skin contact can lead to high electrode-skin impedance, thus it is a potential source of noise.

***9. Examine the data with 24 Hz sampling and with 12 Hz sampling. What happens when you drop below a 20 Hz resample rate?***

The signal looks less like a square wave as the sampling rate is reduced. 24 Hz is the smallest sampling rate that we can observe our 10 Hz signal precisely. As we drop below 20 Hz sampling rate, we started to observe aliasing (e.g. misidentification through undersampling). As stated in the Nyquist theory, sampling at a rate less than double the frequency of our signal results in aliasing. Given our signal's frequency was 10 Hz, resampling at rates below 10 Hz * 2 = 20 Hz (such as 12 Hz) is expected to result in aliasing.

**PART 2: Robot Arm Control using Electromyogram (EMG)**

***10. Describe the changes in the wrist extensor EMG when you extend your wrist against the resistance with the palm facing down. Provide a screenshot of this.***

In the second graph of *Figure 3*, "Wrist Ext (µV)", shown in red, we can see the rises in the amplitude, as the wrist is being extended. We observe an increase ranging from 250 µV to 500 µV above the baseline activity when the wrist extends against the resistor. When the wrist is extended with maximum force, we can observe the peaks on the plot to be close to ±1mV. Therefore, we can conclude that the amplitude of EMG depends on the level of muscle activation. When the action potentials of muscle fibers fire simultaneously, we see larger amplitudes in the electrical potential plot.

The amplitude change rate relates to how fast the muscle contracts. When we extend the muscle quickly we observe that it takes less time for the amplitude to reach its peak (see the second red peak in *Figure 3*), in contrast to applying more force over time (see the first peak in *Figure 3*).

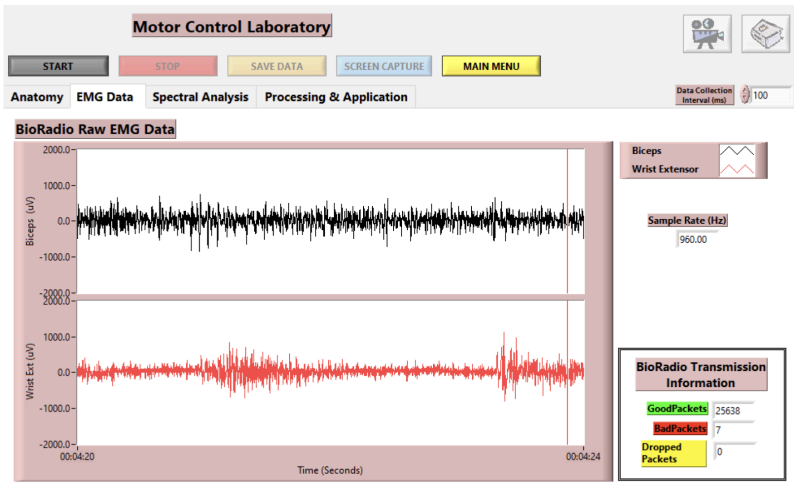


*Figure 3: Wrist Extensor EMG when the wrist is extending*

***11. Describe the changes in the bicep EMG when you flex your elbow against the resistance with the palm facing up. Provide a screenshot of this.***

In the first graph of *Figure 4*, "Biceps (µV)", shown in black, we can see the rises in amplitude, as the elbow is being flexed. Similarly, it shows that the EMG activity in the bicep muscles would have increased significantly compared to the baseline activity when it wasn't flexed. An amplitude rise of approximately 1500 µV is seen when the bicep is flexed with full force. Similar to *Question 10*, the change in amplitude depends on the level of muscle activation due to an increase in the number of muscle fiber action potentials.

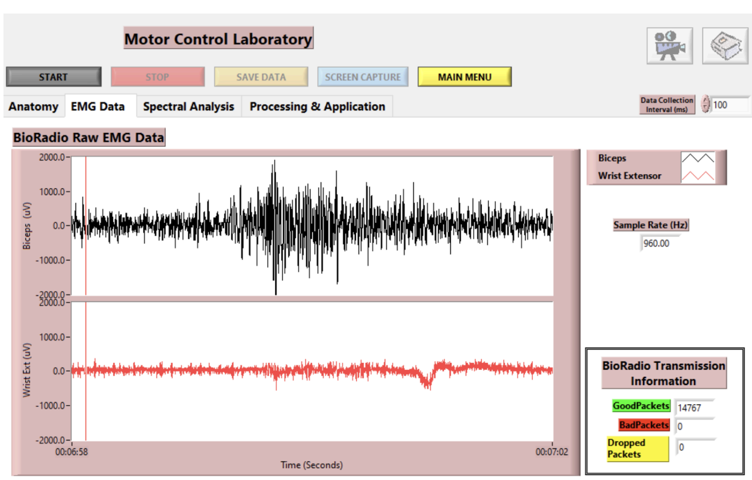


*Figure 4: Bicep EMG when bicep is flexing*

***12. What happens to the raw EMG signal because of a motion artifact due to quick elbow flexion and extension movements? Provide a screenshot of this.***

Due to quick elbow flexion and extension movements, it was observed that the maximum amplitude was reached promptly. These quick movements can introduce high-frequency noise into the EMG signal which likely manifests as spikes or rapid fluctuations in the signal. In addition, during rapid elbow flexion and extension, the muscle and the surrounding skin may move, causing the electrodes placed on the skin to shift slightly introducing motion artifacts. This movement can result in a change in electrode-skin contact impedance and may lead to a brief interruption or distortion of the EMG signal.

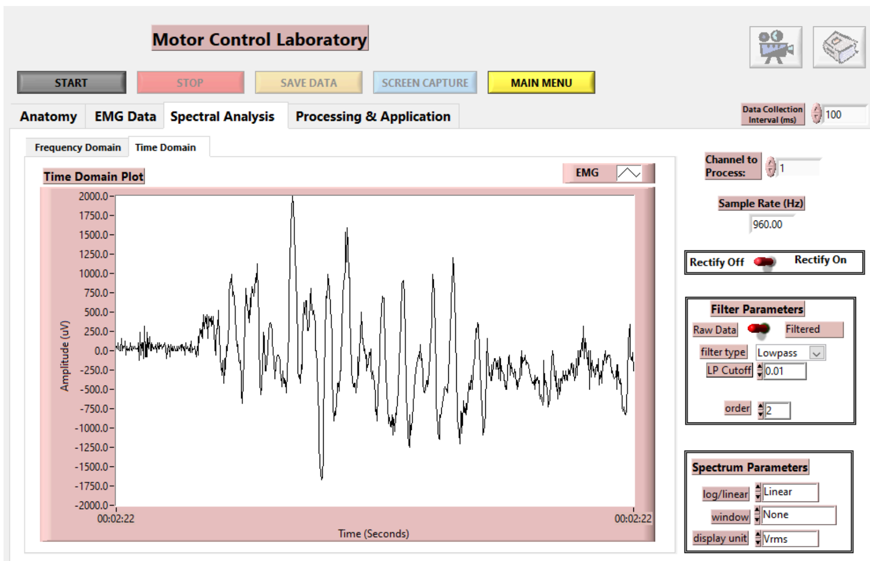


*Figure 5: Raw EMG signal with motion artifact*

***13. With the high pass filter enabled, what happens to the raw EMG signal because of a motion artifact due to quick elbow flexion and extension movements? Provide a screenshot of this.***

With the high pass filter enabled, with regard to the raw EMG signal taking into account the motion artifact due to quick elbow flexion and extension movements, the amplitude remains approximately the same, however, there is a very slight reduction in terms of the noise. Based on the theory provided, the high-pass filter allows high-frequency components, such as the actual EMG signals generated by muscle contractions, to pass through relatively unaffected. This helps preserve the information related to muscle activity. The high-pass filter removes low-frequency noise such as motion artifacts. High-pass filter increases the response time of the system and thereby allows for quick transitions.

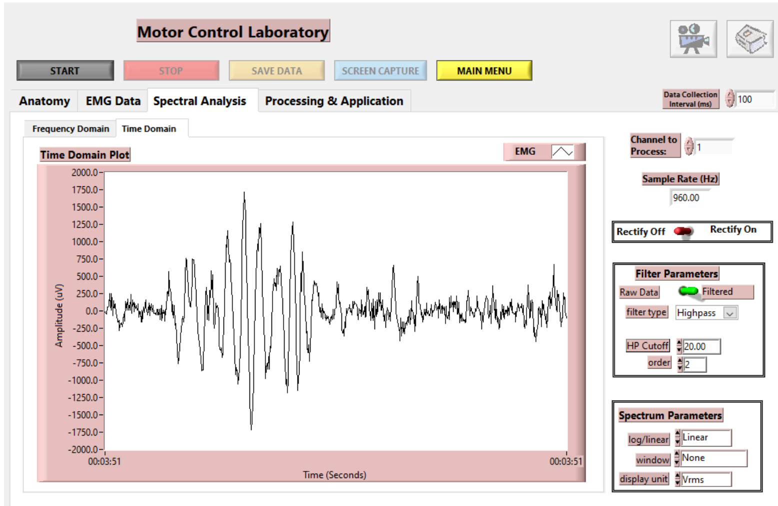


*Figure 6: High-pass filtered EMG signal with motion artifact due to quick muscle flexion*

***14. In terms of control, what are the tradeoffs between high pass and low pass filtering? Why might someone want to high pass filter the EMG data? Think about the frequency range of the EMG signal and sources of artifact in the signal.***

The frequency of EMG signals vary from 0.01 Hz to 10kHz depending on the type of examination.

A low-pass filter removes high-frequency noise and prevents aliasing from occurring in the sampled signal since its typical values are 200 Hz – 1 kHz. When used as a control signal, low-pass filtering provides smoothness to the EMG signal by removing noise and jitter. However, if the high-frequency cut-off point of the low-pass filter is not high enough, we won't be able to detect rapid changes in the EMG signals.

A high-pass filter increases the response time of the system and thereby allows for quick transitions. Typical values for the low-frequency cutoff are 5 to 20 Hz. It removes low-frequency noise including artifacts associated with movement and perspiration, and removes any DC offset. Therefore high-pass filtering EMG data is useful when analyzing rapid changes in the muscle responses. When the high-pass filtering is applied the mean value would be close to 0 since it removes the low frequency signals. Therefore, using high-pass filters can cause a loss of important information where the low-frequency signals are relevant to the analysis.

One might want to use high-pass filters when analyzing muscle force and response since using this type of filter effectively removes artifacts caused by movement and perspiration.

***15. What are the normalized wrist extensor and bicep control values for achieving complete relaxation? Is the robot arm extended with claw open? Provide a screenshot of this, showing both the arm and the control values.***

Normalized relaxed wrist extensor control value: 0.0

Normalized relaxed bicep extensor control value: 0.0

As seen in the screenshot in *Figure 7*, the robot arm is extended with the claw open.

Although these normalized relaxed control values seem correct, we want to mention that these values were fluctuating and the screen capture may have defaulted to 0.0.

As seen on the "Normalized Control Signals" graph in *Figure 7*:

1. The relaxed biceps signals are accurately and consistently near zero.
2. The relaxed wrist extensors do not perform as accurately due to noise, however, the average signal is around 0.25.

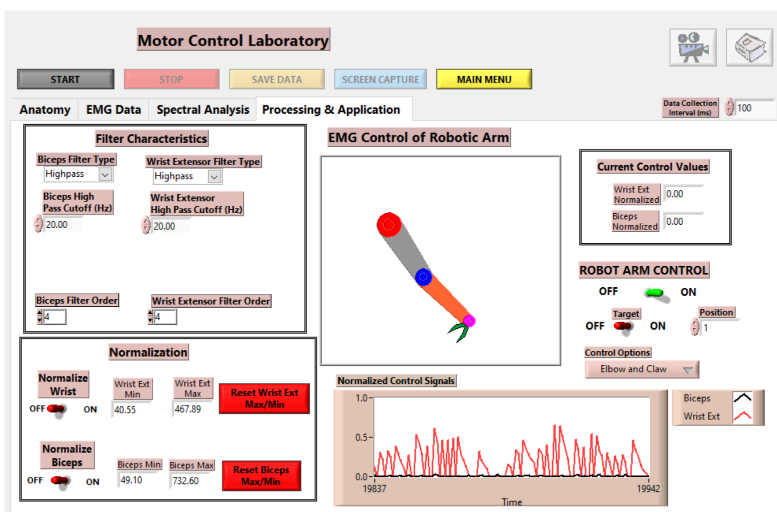


*Figure 7: Relaxed biceps and wrist extensors*

***16. What are the normalized wrist extensor and bicep control values for achieving maximum contraction? Is the arm flexed with the claw closed? Provide a screenshot of this, showing both the arm and the control values.***

When we tried contracting both muscles at the same time, the robotic arm flexed and the claws closed only partially as seen in *Figure 8* and we received the following values:

Normalized contracted wrist extensor control value: 0.0

Normalized contracted bicep extensor control value: 0.0

As mentioned in *Question 15*, these normalized control values were fluctuating and the screen capture may have defaulted to 0.0. For example, in all the BioRadio software's screen captures the control values show 0.0, whereas in our pictures from our phones, we capture non-zero control values shown in *Figures 9* and *10*.

Ideally, we were expecting our normalized contracted control numbers to be closer to 1.0 since higher levels of muscle activity were expected to result in a higher amplitude. However, we weren't able to receive this result due to the high level of noise in our EMG signal due to artifacts caused by the movement of both muscles.

When we contracted the biceps and wrist muscles separately, we were able to achieve the desired results. The closed claw can be seen in *Figure 9* with the normalized contracted wrist extension value of 1.0 and the flexed robotic arm can be seen in *Figure 10* with the normalized contracted bicep extension value of 0.63, which is relatively close to the maximum normalized value of 1.

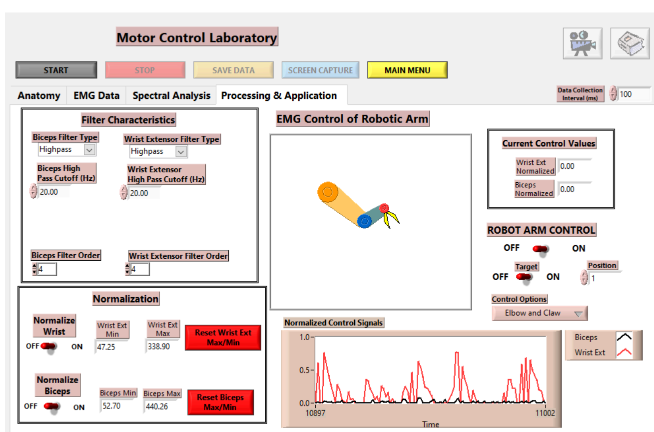


*Figure 8: Partially closed claw and flexed arm with contracted biceps and wrist extensors*

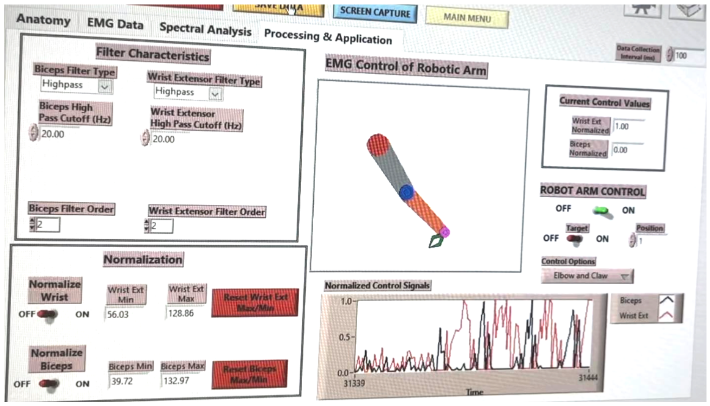


*Figure 9: Closed claw with maximum wrist extensor contraction*

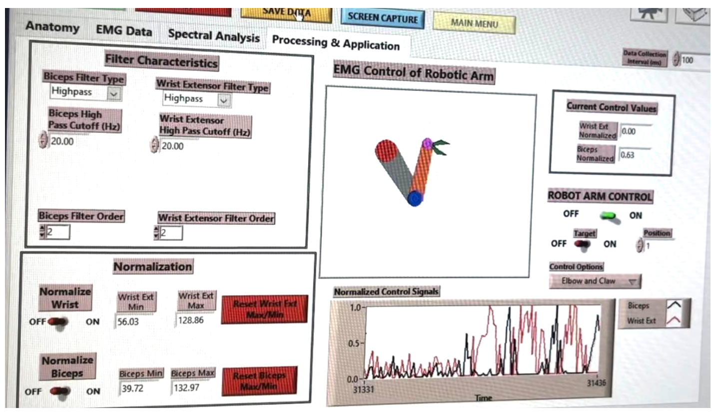


*Figure 10: Flexed arm with "maximum" bicep extensor contraction*

To normalize the wrist extensor EMG signal more accurately, we tried reducing the noise by modifying the placement of electrodes and changing subjects to prevent the effects of muscle fatigue. However, the signal remained as noisy as before.

***17. Describe how changing the filtering parameters affect control of the robot arm. (I.e. how the smoothness of control changes as a function of the filter type and cutoffs or how the transition speed of the control changes as a function of filter type and cutoffs.)***

The filtering parameters in the control of a robot arm were observed to have significantly impacted the smoothness of control when using low-pass and the speed of transitions in the control of the robot arm when using high-pass.

In comparison to our control signal with high-pass cut-offs at 20 Hz in *Figure 8*, we can observe that changing the filter to low-pass in *Figure 11* provided smoothness to the signal. When applied low-pass filter with cut-off frequency of 10 Hz, we observed aliasing, therefore inaccurate control of the robotic arm. Increasing the cut-off of the low-pass signal from 10 Hz to 100 Hz, we observed more peaks in the signal, since increasing the cut-off point allowed more low-frequency signal data to pass through, introducing more noise and jitter to the signal. A cut-off frequency of 30 Hz for bicep EMG provided us with the most amount of precision when controlling the robot arm when slowly contracting the muscle and we were able to achieve the desired movements as seen in *Figure 13*.

By increasing the cut-off frequency of the high-pass filter, we were able to remove noise that was caused from motion artifacts when extending the wrist muscles. As seen in *Figure 12*, by increasing the cut-off frequency from 10 Hz to 30 Hz, we were able to see peaks that correlate to maximum flexion of the muscle as the transition speed of the control increased. Using this type of filter provided an increase in the response time to allow for quick transitions. As our wrist signal had a significant amount of noise due to motion artifacts, increasing the cut-off frequency of the high-pass filter enabled us to observe the closed claw seen in *Figure 13* when the maximum flexion of the wrist muscle was achieved.

For the low pass-filter, when applied to robot arm control signals, it smoothed out some of the rapid, high-frequency variations in said signals. Using a high-pass filter in robot arm control slightly made the arm more responsive to rapid changes in control commands.

The low-pass filter with lower cut-off frequencies appeared to provide some smoother but slower movements, whereas the high-pass filter with higher cutoff frequencies displayed faster but less smooth control.

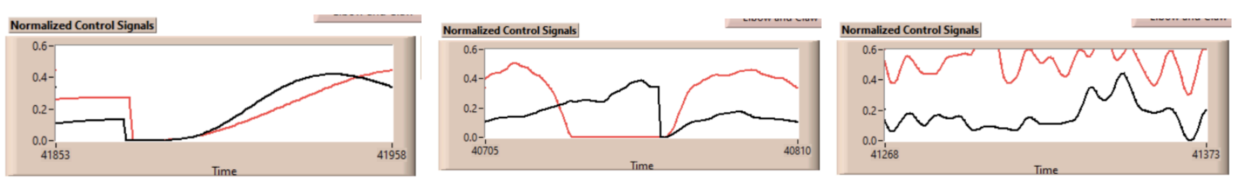


*Figure 11: Low-pass filters with cutoffs 10 Hz, 30 Hz, and 100 Hz (left to right)*

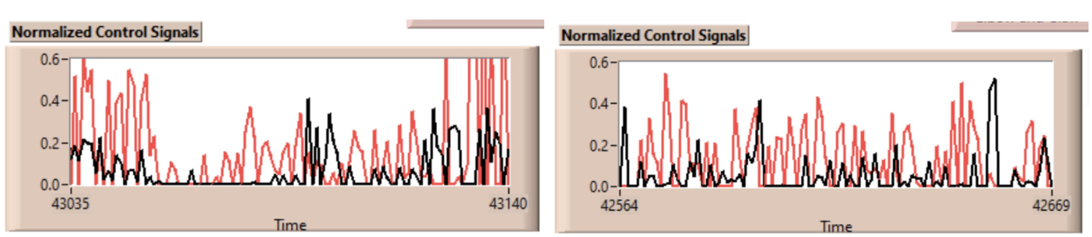


*Figure 12: High-pass filters with cutoffs 10 Hz, and 30 Hz (left to right)*

Through experimenting with high-pass and low-pass filters with various cutoffs,  we were able to achieve the desired result of the flexed arm with a closed claw as a result of maximum contraction in biceps and wrist extensors, which can be seen in *Figure 12*, by choosing:

- a low-pass filter with a 30 Hz cutoff for the biceps,
- a high-pass filter with a 60 Hz cutoff for the wrist extensors, and
- filter orders of 2.

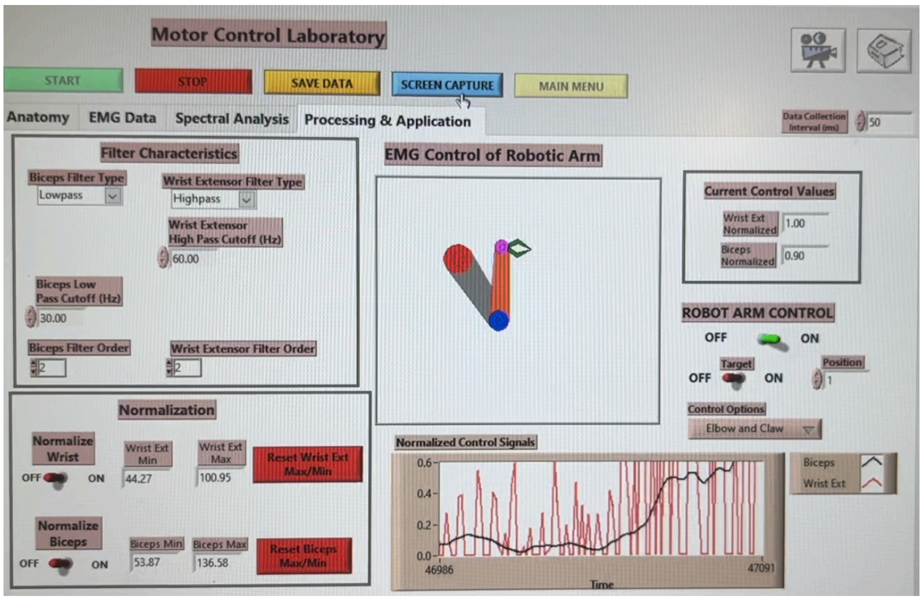


*Figure 13: Flexed robotic arm with closed claw due to maximum contraction of muscles*

***18. Describe the effect of increasing and decreasing the data collection interval on your ability to control the robot arm.***

When the data collection interval increased, the robot arm became less responsive to our control inputs. As mentioned in *Question 3*, this can be attributed to the robot arm receiving real-time control updates less frequently, thereby resulting in a less frequent response. In contrast, decreasing the data collection interval, the robot arm became more responsive to our control inputs, as it received data more frequently.

***19. Often times in biomechanics, transducers are used to record the angle of a joint during motion. Explain why even a small amount of noise in the signal may prohibit someone from calculating the angular velocity and acceleration of the joint using the angle data from the transducer.***

Calculating angular velocity and acceleration involves taking derivatives of the angle signal with respect to time. This means that any noise or fluctuations in the angle signal will be amplified when calculating these derivatives. Even a small amount of noise in the angle data can result in relatively large errors in the calculated velocity and acceleration values. These errors introduced during differentiation accumulate over time. This means that the impact of noise becomes more significant as you differentiate the signal to calculate acceleration.

**Summary of Results & Discussion**

In Part I of this lab, we observed the signal generated from the BioRadio Test Pack and plotted different types of noise to observe their characteristics. We investigated the effect of data collection intervals and sampling frequency on the data acquisition process and tested the range of the BioRadio transmitter/receiver pair. Thereby, we gained a better understanding of the capabilities and limitations of the BioRadio system. In Part II of this lab, we collected electromyogram (EMG) signals, which record the electrical activity of muscle tissue, by placing electrodes on the biceps and wrist extensor muscles of our subject. Using the CleveLabs software, we used these EMG signals to control a robotic arm model. We investigated ways to eliminate noise from our signal by simulating filtering techniques, to eliminate certain frequency levels, in order to achieve more precise movements in the robotic arm control. We observed that while removing high-frequency signals provided smooth control and noise removal for the bicep EMG signal, removing low-frequency signals performed better to get rid of noise due to motion artifacts in the wrist EMG signal, as it allowed for quicker transitions in control.