BME 111: Project 3 Writeup
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Part 1

When recording ECG data, we varied physical and mental activity to observe the heart rate variation under different kinds of stress. We placed three sensors on Rowan's chest, and tried to choose activities that limited motion. Limiting motion is important to decrease the chance of artifacts, from his shirt moving on the sensors, and from the motion of his body. Our four activities included sitting at rest, watching calm youtube, playing a video game, and performing a wall sit.

By monitoring the data as it is measured through the serial monitor, we ensured it was high quality and not encountering inaccurate recordings or experiencing many artifacts.

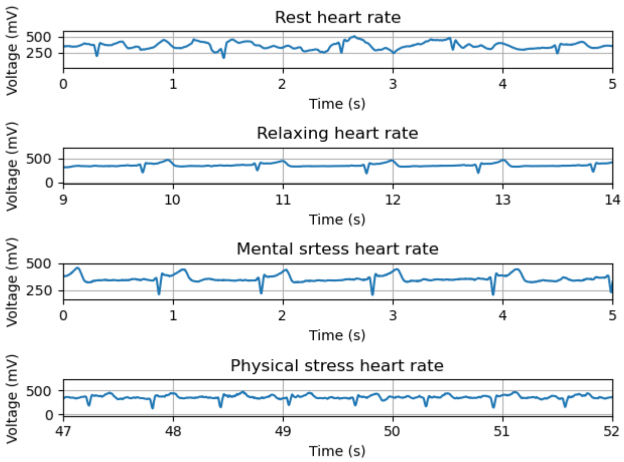

Figure 1: Unfiltered ECG data in mV.

By concatenating the signal we brought all four data sets into one signal. The plot of all four signals is able to show how artifacts affect the overall data. When recording the physically strenuous data we saw a large artifact at the end of the five minute recording. It affects the other recordings by increasing noise in an otherwise clean signal.

The function load_data takes in a .txt file of floats to read into an array. The duration and sampling frequency can be modified to varying signal length, and are taken in as variables. This function can take in any text file and vary the duration and sampling frequency, allowing for flexibility In how many samples are desired in the final data set.

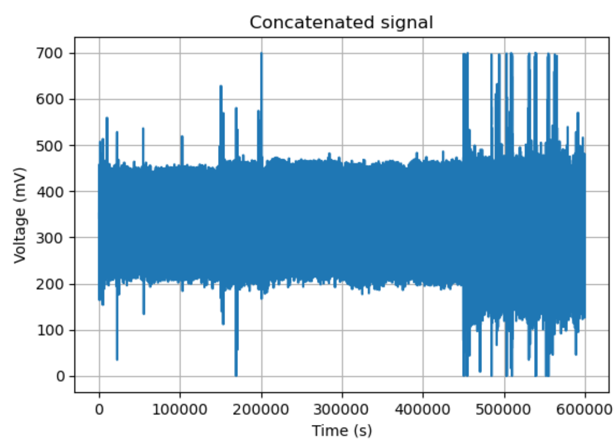

Figure 2: Concatenated Data

Part 2

We chose a bandpass filter that filters out noise above and below the desired frequency range to get rid of low frequency drift and high frequency fuzz. Only looking at the central frequencies we chose allows us to only focus on the frequencies caused by the heart, and eliminate signals that are out of range of a normal heart beat range, 60-100 beats per minute. We ended up choosing a broader range of 30-150 bpm as the filter performed better. This impulse response of the filter as

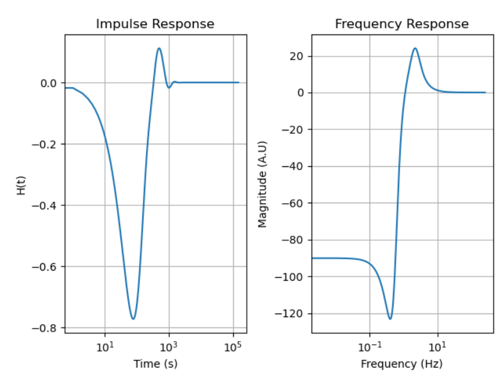

Figure 3: Impulse and Frequency of Bandpass Filter

seen on the right of Figure 3 shows that all values are zero except for the specified range set in the bandpass filter.

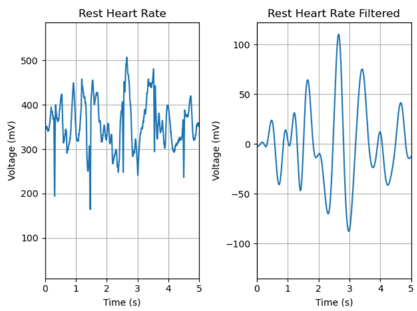

Figure 4: Filtered vs Unfiltered Rest ECG Data

Figure 4 represents the effect of this filter on the signal showing the reduction of noise, the smaller peaks throughout the signal, as well as the drift.

We expect this filter to clean up our data, and return a signal only representing the subject's heart beat. Our function filter_butter takes in a signal and applies a band pass butter filter by attenuating signals that are out of range of a normal heart beat. This filter returns a 1D array of the filtered signal. The user is allowed to set the low cut and high cut frequencies, the sampling frequency, the order, and type of the butter filter to customize it to their own data set.

Part 3

Now that our signal is filtered, and only represents the subject's heart rate. Knowing that the voltage of the R wave of a QRS complex tends to be higher than the surrounding values, a threshold can be set to identify where a heart beat occurs.

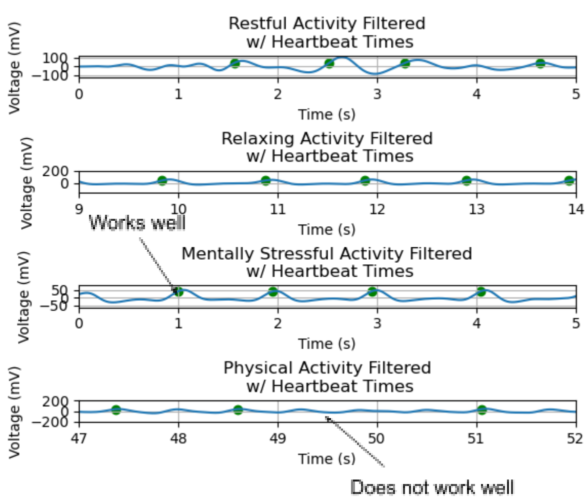

Figure 5: Marked Heart Beat On Filtered Signal

The function detect_beats takes in a signal, threshold, and sampling frequency, and returns two 1D arrays of consistent beat_locations, and beat_times. These values can be used to mark the site of beats on a graph of the filtered signal. Using boolean indexing, all values that surpass this threshold will be added to an array, beat_locations. This array can be used to index both a time array, the same length of the signal, as well as the original signal to determine which values represent the beats. This function can take a signal of any length, the threshold can be specified, as well as the sampling frequency.

Part 4

Figure 6 of the HRV values shows the standard deviation calculated from the interpolated IBIs for each kind of activity. We predicted that the HRV would be larger, or the IBIs would be more variable under stressful events. As shown in the figure physical activity shows the highest amount of variation, though it is followed by rest rather than the mentally stressful activity. The degree of variation seen in the physical activity represents the increase in heartbeat throughout the five minute exercise, which is what we expect to see. The variation in rest is due to inaccurate data collection and the presence of artifacts, and since it was the first data set recorded there was more error present. As we collected more data we became proficient at eliminating mistakes and decreasing inaccurate data collection.

The function calculate_ibi's not only calculates the signals interbeat interval, but also the HRV. By taking in the beat_location and beat_times arrays the function is able to create an array of the detected beats, connected by linear functions through interpolation. The HRV can be calculated from this array by taking the standard deviation and stored in the variable HRV. The sampling frequency, dt, and beat locations are all to be specified each time the function is called, and can work with any length signal. This function returns a 1D array of the interpolated signal, as well as the HRV value stored as a float.

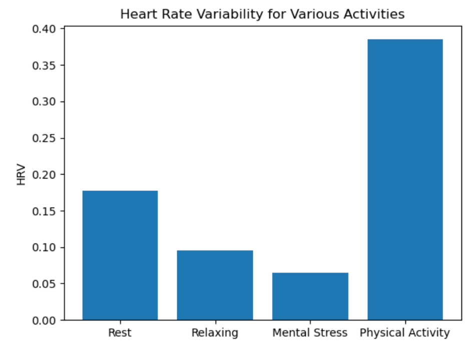

Figure 6: Heart Rate Variability for Various Activities

Part 5

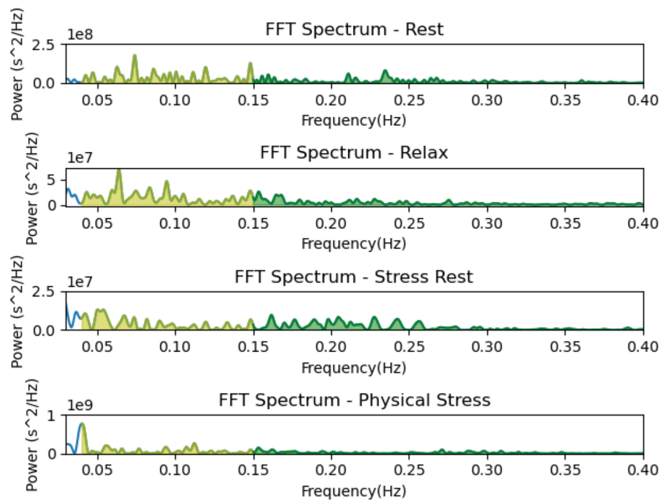

Figure 7: FFT Spectrum of Various Activities

Figure 7 shows the high frequency (HF), shown in green, and low frequency (LF) bands, shown in yellow, present in each activity. The bar chart in figure 8 shows the ratio of these low and high bands as a value representing LF/HF. If high frequency signals represent activity in the parasympathetic nervous system (PNS), the ratio will be lower for activities that require brain activity. If the sympathetic nervous system (SNS) is represented by low frequency values then physical stress will be represented by a larger LF/ HF ratio.

Figure 8 supports these assumptions and follows the trend we expect to see for PNS and SNS activity. The mentally stressful activity has the lowest LF/HF ratio of the four shown, representing the brain activity detected when increasing PNS activity. Similarly to this idea the physical activity shows a high LF/HF ratio, representing the large low frequency presence during times of increased SNS activity due to physical exercise. Relaxing follows this same trend by picking up on the physical movement, though minimal, required to play video games.

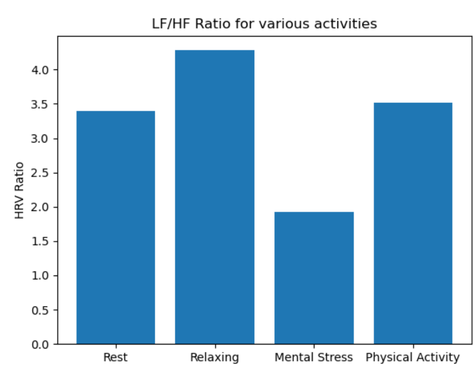

Figure 8: HRV Ratios

The function frequency_filter separates the frequencies into low and high groups based on specified threshold to calculate the mean power of each band. These thresholds define high and low cut off frequencies for PNS and SNS activity detected in heart beats. This function takes in an array of the interbeat interval values and dt and returns multiple arrays that are able to define the frequency and power for the signal, low frequencies, low powers, high powers, and high frequencies. By taking a fourier transform of the interbeat intervals we were able to calculate each signal's power, determine low and high frequencies and add them to two individual arrays. These ratios are then plotted and color coded to visually see the LF/HF ratio. This function is able to run with any signal, dt, and thresholds.

The function extract_mean_power takes in the power values previously calculated for low and high frequencies and finds their mean. To create figure 8, the ratio of the two mean values is found by dividing the low frequency by the high, and returning this ratio as a float that can be graphed against the other activities. This function has no set values and can operate with any 1D array.

Part 6

Side note: Alta and I had different interpretations of our LF/HF ratios being able to indicate PNS/SNS activity, so this response is a bit different from some of the points she brought up in part 5. -Lauren

Due to the knowledge that a higher LF/HF ratio indicates that the sympathetic nervous system is dominant, our results would conclude that the sympathetic nervous system was most active during the relaxing activity, and interchangeably the parasympathetic nervous system was most active during the mental stress activity where a low LF/HF ratio was calculated. The HRV ratios for the resting activity and the physical stress activity were similar, which was unexpected considering that the body is under more stress while performing an exercise than while sitting still. Our results do not support the position that HRV's LF/HF ratio can be used to index stress. During the first two activities, the subject was at rest, implying that their parasympathetic nervous system should have been dominant. During the last two activities, the subject was under mental and physical stress, which would mean that their sympathetic nervous system should have been activated. The average HRV ratio of the first two activities is ~3.75 while the average for the second two is ~2.5. According to these values, there would have been sympathetic dominance during the first two activities and parasympathetic dominance during the second two, which contradicts what is known about the ANS.

One factor that could be limiting this conclusion is the fact that we don't actually know what the subject was experiencing during each test. For example, if the subject was feeling anxious during the first two tests and then had relaxed for the last two, it would make sense that the HRV ratios of the first two activities are a bit higher. An anxious state is definitely dominated by the sympathetic nervous system so the idea that the LF/HF ratios can indicate the presence of these two systems could be valid. Another factor could be errors that were made when calculating the interpolation of the IBIs. An error in this data would lead to inaccurate frequency and power values after doing the FFT into the frequency domain. This in turn would affect which power values were included in the high and low frequency bands, and ultimately the ratio of LF band power to HF band power. Some ways in which we could improve are choosing activities that are *guaranteed* to induce either a state of stress or relaxation on the test subject. Another way to improve would be comparing the interpolated IBI values with a set of accurate IBI values from a research article that could have done something similar. This way we could see if the error lies in the interpolation, or at another step.

The way in which artifacts are affecting our results is especially clear in Figure 2 of the concatenated signal. There are large fluctuations in voltage, especially at the end of the signal, which could be caused by a number of artifacts. There could have been some body movement artifacts at any point in data collection, because even at rest the body is not completely still. Artifacts also could have been caused by the subject's clothes brushing up against the sensor, or their body hair. An additional source of artifacts could be power lines which are large sources of electricity. The final results could reflect these artifacts, because each step in this project builds on the last one. Therefore if an artifact affected our ability to accurately detect heart beats, then this would lead to an inaccurate IBI timecours, HRV, and HRV ratio. Data collection could be improved by having the test subject shave where the sensors were placed and also remove any clothing that could be in contact with the sensors. To get rid of any power line artifacts, a notch filter could be used to remove 60Hz activity. With more time, there could have been more detailed filtering specific to the amount of drift/fuzz in each dataset. With more time/resources there could have also been a closer analysis of our data at each step and comparisons to scientific articles that detailed the same process. This would ensure that there were no errors building on each other.