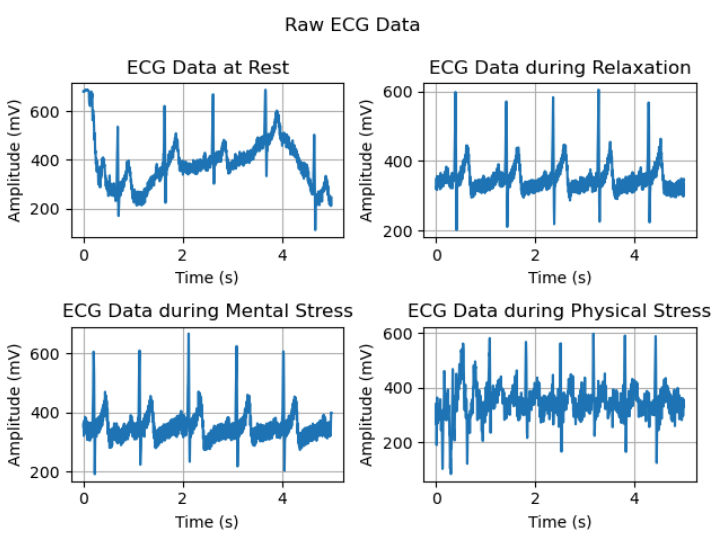
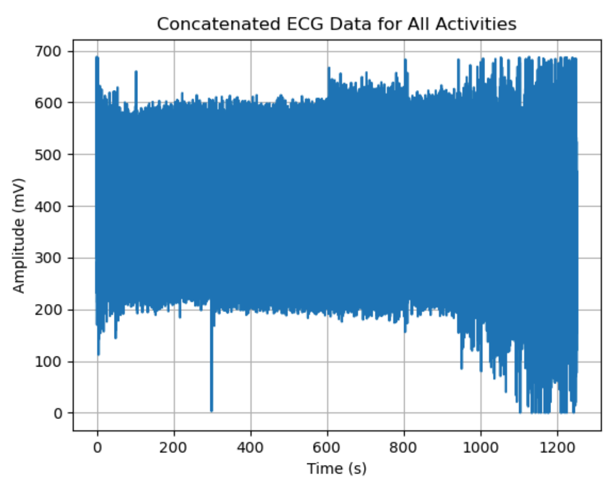
BME Core 3
Project 3 Writeup
Anya Bobkoskie

Part 1: Collect Data

The four activities performed for data collection were sitting at rest (rest), watching puppy videos (relaxation), playing chess (mental stress), and planking (physical stress). These activities were chosen based on the fact that they can all be done with little to no movement, and therefore have a lower chance of producing artifacts and noise during data collection. In order to collect high quality data, measures were taken to ensure that the electrodes were placed adequately. The electrodes were placed on both forearms and upper right leg, as the diagram indicated on the website for the device. Leg hair was removed and the sites of attachment were wiped with alcohol before electrode placement, and once placed it was ensured that the electrodes were in full contact with the skin. As mentioned before, motion was limited during data collection, and the data was collected in a private room with little environmental interference (electrical equipment, external forces). In order to check that this data was high quality, the data was graphed and inspected for normal ECG shape (P-wave, QRS complex, T-wave). It was also inspected for any obvious artifacts such as large spikes or flat lines. Most of the data was found to be high quality throughout, with the exception of the physical stress activity data. Since the physical stress activity was a plank, there was a lot of shaking that produced noise during data collection. The overall ECG shape can still be made out in the first half of the dataset, but the second half is significantly more noisy. Unfortunately, due to time and resource constraints, we were unable to re-record this data.

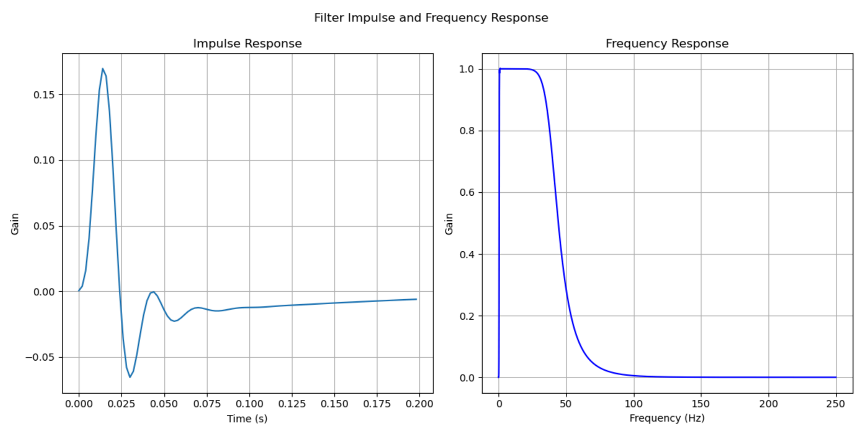




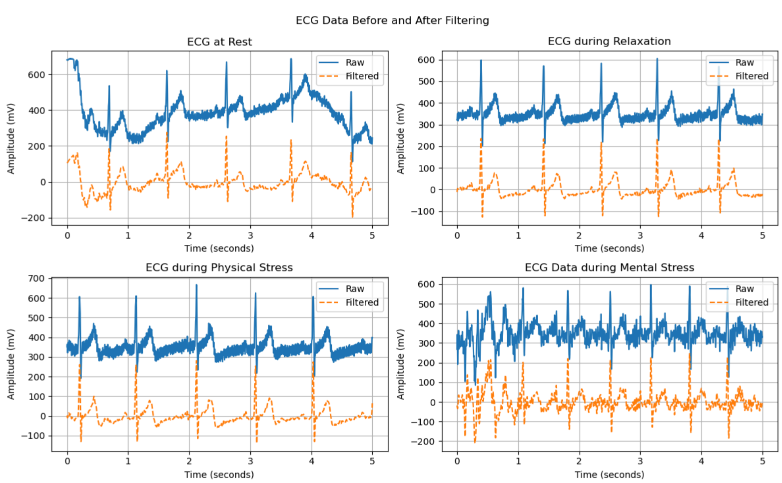
The figures above show all of the ECG data that was collected during this experiment. The figure on the left shows the first five seconds of ECG data for each of the four activities plotted separately. The figure on the right shows the concatenated ECG data for all of the activities together. This concatenated plot is meant to see if the activity changes are visible, which is not exactly the case although it can be seen that the stressful activities plotted last (specifically the physically stressful activity) has a greater range of amplitudes in its data.

There was one function created in the module for part 1, which was called plot_ecg. This function takes a signal's dataset and plots it over time. The function is flexible enough to work in multiple situations because it can take any signal, make a time array for it based on the sampling frequency input (fs), and plot that signal over time. Additionally, it plots the signal for a specified duration based on input and it gives the plot a title that is also based on input.

Part 2: Filter Data



The figure titled 'Filter Impulse and Frequency Response' on the right shows the impulse and frequency responses of our filter. A bandpass butterworth filter was used to filter the data for several reasons. We chose a bandpass filter because it is able to retain frequencies between 0.5 and 40 Hz, which are most relevant for an ECG signal, and filter out both low-frequency and high-frequency noise. We chose a butterworth filter because it is an IIR filter, which requires less processing power and has sharper cutoffs compared to a typical FIR filter which could help ensure that only necessary frequencies are retained. Additionally, we chose a butterworth filter instead of a different IIR filter such as a Chebyshev because it is a smoother filter that introduces less distortion to the original signal when filtering.

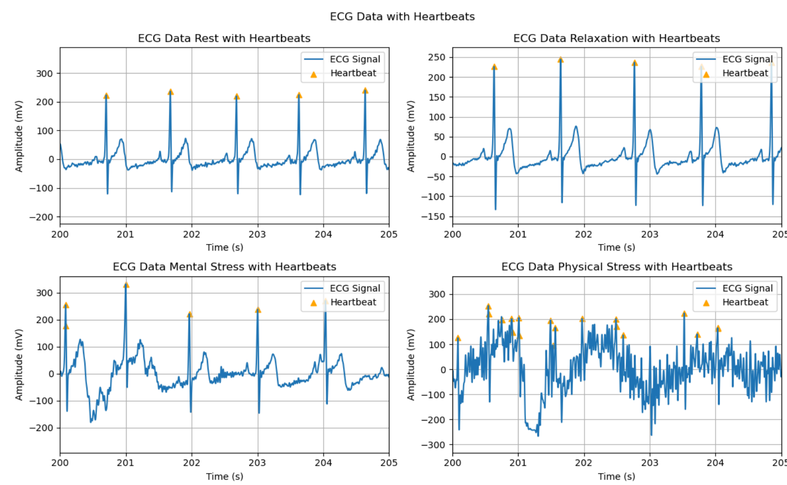


The figure titled 'ECG Data Before and After Filtering' shows the ECG signals of each activity before and after filtering was applied. It can be seen that the filter worked as expected for the most part. Based on our inputs, we would expect the filter to keep data recorded at frequencies between 0.5 and 40 Hz, making the filtered data appear less noisy (ripples) and also reduce baseline wandering. These seem to be met based on the graphs with both filtered and unfiltered data, although it is hard to tell exactly which frequencies are kept in the signal by looking at the plot. There are clearly less ripples in the filtered ECG data, and the baseline wandering looks to be reduced as well since the filtered data is centered around 0 mV, unlike the raw data.

There were two functions written in the module for this part of the code. The function bandpass_iir_filter uses a bandpass butterworth filter to filter a given dataset. There are default cutoff frequencies (0.5 and 40 Hz), sampling frequency (500 Hz), and order (5), although the code is flexible as it allows any of these defaults to be changed based on input. The function plot_before_after_filtering plots both unfiltered and filtered data together. It is flexible by allowing for input on the duration of the graph, as well as sampling frequency input in case a signal has a frequency that is different than the 500 Hz used throughout this project.

Part 3: Detect Heartbeats

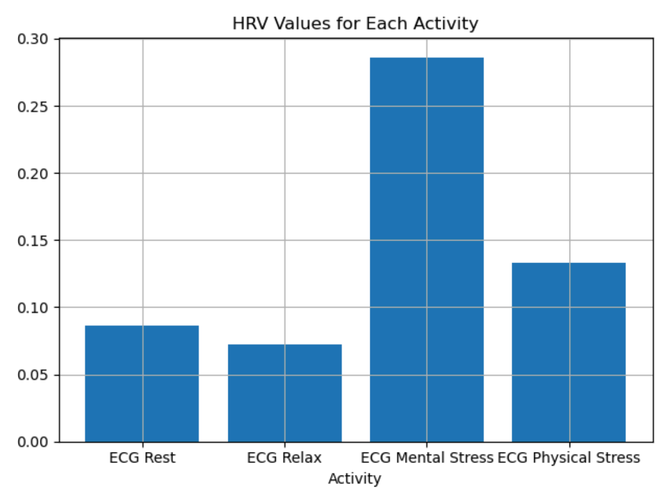
To detect heartbeats in our ECG datasets, we imported a python toolkit called HeartPy. This toolkit has many functions that can be used to analyze heart rate data. One of these functions is called process and it can be used to process the data that is given and obtain certain information from it such as a ‘peaklist’ that detects each peak in the data. We used this function to get each peak in the ecg datasets and define those peaks as heartbeats. We chose to use this method because it is simple and it comes from a reliable toolkit that is used often when analyzing heartbeats.



The figures on the right show that the detection method works well when the ECG data has a clear shape and little noise, but when there is lots of noise in the data the method does not work as well.

The only function written in this part of the code was plot_heartbeats, which uses HeartPy to detect heartbeats and plot them, and returns the times of each heartbeat detected. Similar to the plot_before_after_filtering function, it is flexible by allowing input for duration of the graph and sampling frequency.

Part 4: Calculate HRV

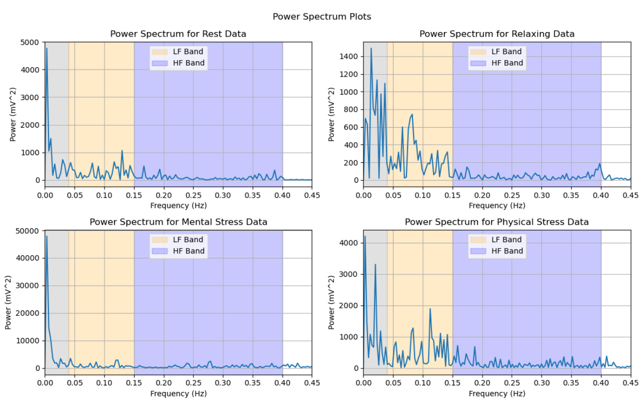


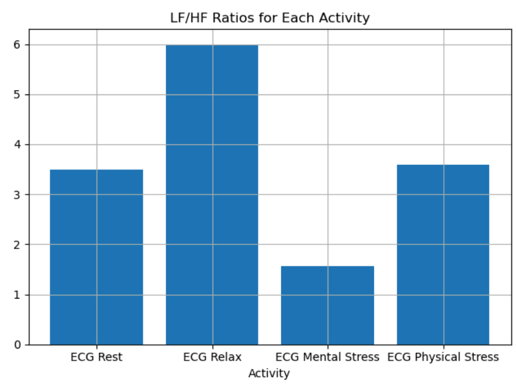
The barplot on the left shows respective heart rate variability (HRV) values for each activity recorded during this experiment. It can be seen that HRV values were calculated to be higher during the stressful activities, particularly the mentally stressful activity, than the relaxing ones. The mental and physical stress activities produced HRV values of about 0.28 and 0.13 respectively, while the rest and relaxation activities produced HRV values of about 0.09 and 0.07 respectively. This goes against our expectations that

HRV values would be lower during stress. Generally, during stressful activity the sympathetic nervous system is activated, causing a higher heart rate and reduced variation between heartbeats. These unexpected values could be due to errors in our heartbeat detection method, or they could be due to the fact that the data was not recorded for a long enough time period to accurately calculate HRV.

Two functions were written in this part of the code. The first function, calculate_ibi_hrv, calculates the inter-beat intervals (IBI) and HRV from an array containing heartbeat times. This code is flexible in the sense that it can calculate IBIs and HRV for an array of any size that includes heartbeat times. The second function, interpolate_ibi, interpolates a set of IBIs to get them at regularly spaced times. It is flexible because it works for any length set of ibis and heartbeat times, and although it has a default interval of interpolation of 0.1 seconds, this can be changed via input.

Part 5: HRV Frequency Band Power





The plots on the left above titled ‘Power Spectrum Plots’ show the power of both low frequency and high frequency activity in each ECG signal, based on the fact that low frequencies are 0.04-0.15 Hz and high frequencies are 0.15-0.4 Hz. The plot to the right titled ‘LF/HF Ratios for Each Activity’ shows the ratios of low to high frequency power for each activity. Since low-frequency power typically indicates more SNS activity and high-frequency power typically indicates more PSNS activity, we would expect the ratios to be higher for stressful activities. However, this is not the case. We can see that the ratios for rest and physical stress are both around 3.5, while the ratio for relaxation is up near 6 and the ratio for mental stress is only about 1.5. Again, these values not meeting our expectations could be due to errors in heartbeat detection, bad filtering, or low-quality data.

The only function written in this part of the code was the frequency_band_power function. This function plots the power spectrum of an activity by calculating the FFT of its interpolated IBIs and squaring those values to get power. It also calculates the LF/HF ratio for the activity and returns it as a variable. It is flexible because it can take any sized array of interpolated IBIs, and the default values for interpolation interval, LF band, and HF band can all be altered.

Part 6: Reflect

Our results support the position that LF/HF ratios do not reflect stress levels, as there was no conclusive evidence one way or another indicating that stress is associated with these values. There were many possible limitations to this study, one being that the ECGs were not recorded for a long enough time period to get solid data. Also, it must be understood that the quality of the data used in this project was not the best, and noise and artifacts could have led to inaccurate data during analysis. One way we could improve our data analysis in future studies would be to improve our filter. A filter with sharper cutoff frequencies could allow for more accurate filtering-out of noise. We could also improve our results by collecting better data initially, perhaps by using more high-end equipment that is better at reducing noise and artifacts. Finally, data being recorded for longer time-periods could help us get more accurate numbers for HRV and IBIs, which are essential values in this analysis. Overall, this study was not perfect and there is much room for improvement in future projects.