BME 3000A
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Evaluation of ECG Data During Different Activities

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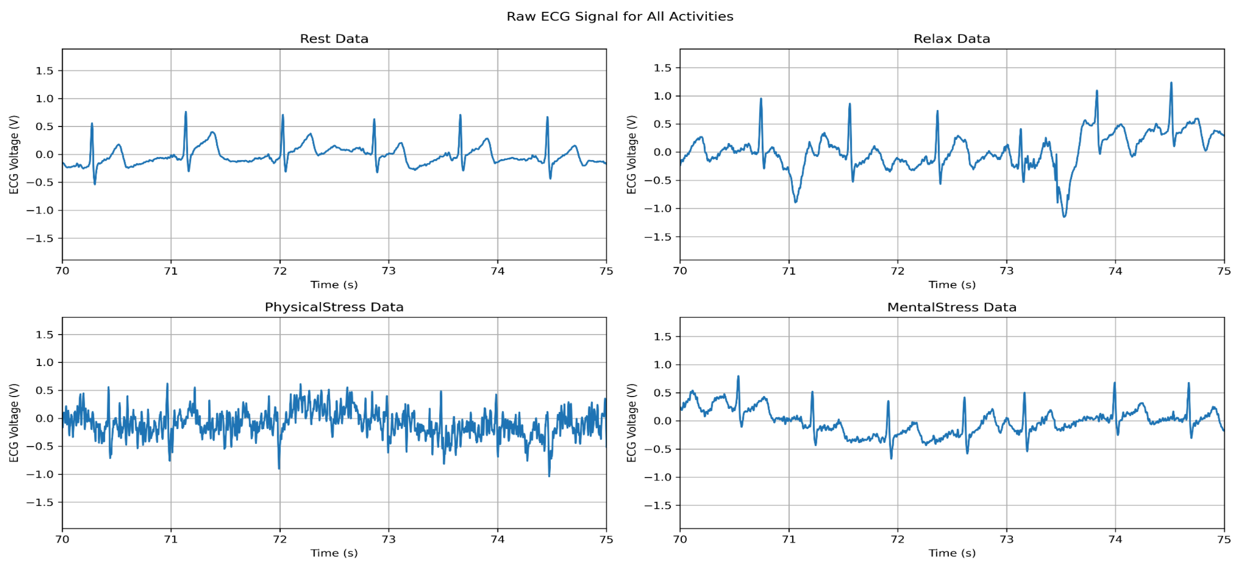
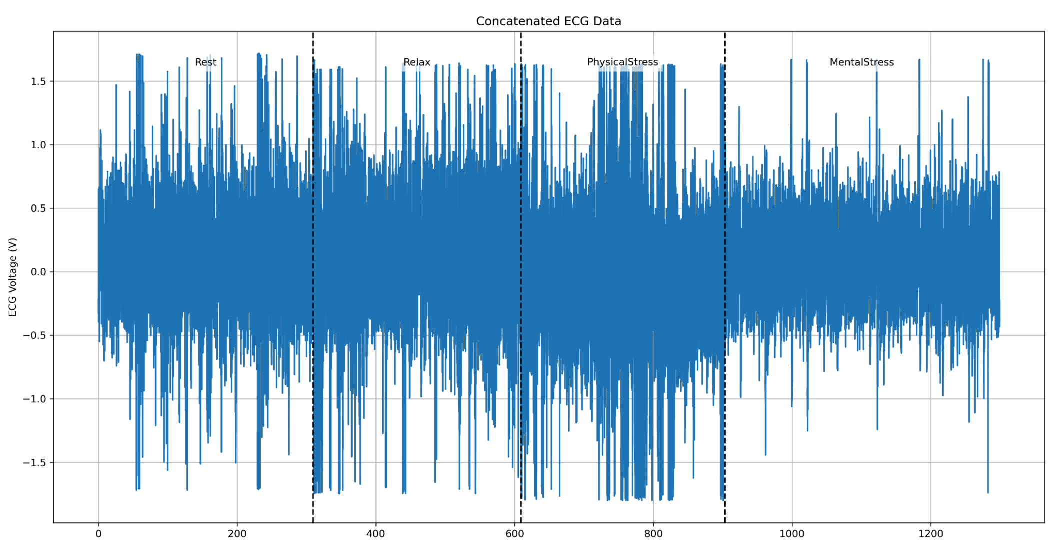
Part 1: Collecting our data

To collect the data, electrocardiogram(ECG) leads were placed on the subject according to Einthoven's triangle. We observed that any limb movement caused the data to zero out in the Arduino software, because of its built-in voltage limits. To minimize this, we asked the subject to limit movement during recordings. Four tests were performed: a resting phase where the subject sat and talked for 5 minutes, a mentally relaxing activity where the subject listened to music and talked, a mentally stressful activity involving playing Clash Royale, and a physically stressful wall sit. Some movement occurred in each trial. The least movement was in the mentally stressful activity and the most in the physically stressful one. The concatenated data shows the mentally stressful trial had the fewest large voltage jumps, while the physically stressful trial had the most.

Plots:



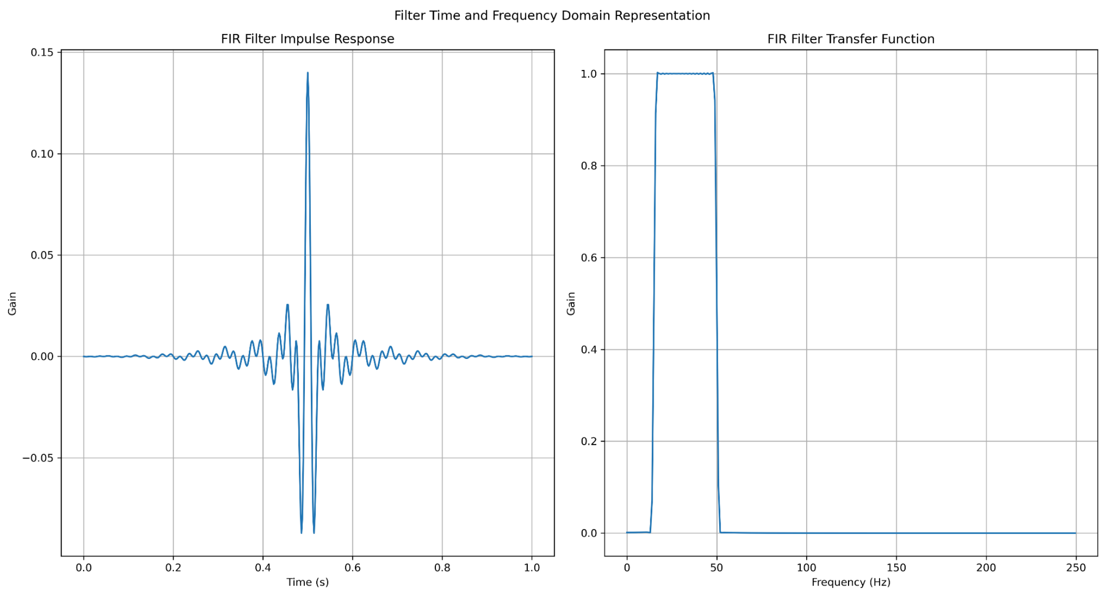


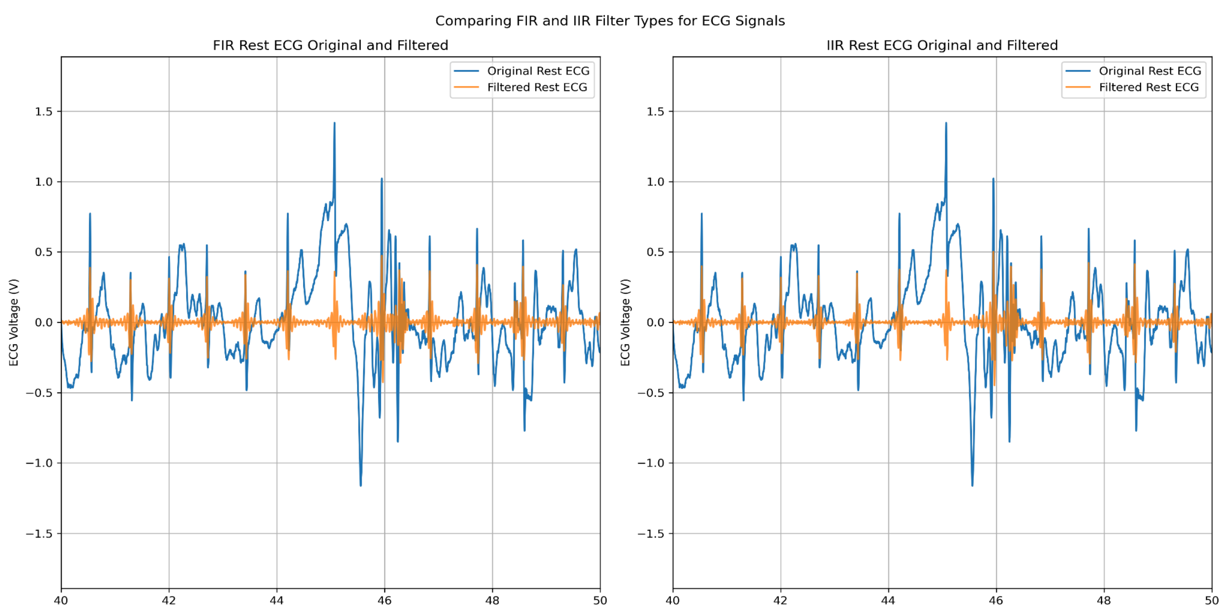
Functions: Our first function, load_data, loaded and normalized the data from the text files for each activity. It is flexible because modifying the scaling would allow it to be used for other time-series datasets. The adjustable sampling frequency input also adds flexibility. Our second function, establish_figure, creates a new figure and updates the figure count for the program. This results in flexibility by automatically updating the figure count as the program runs, allowing a new figure to be inserted anywhere in the program without having to adjust anything else. Our third function, plot_data, typically plotted ECG data against time. This function is flexible because it standardizes the plotting process, allowing the user to plot any data as long as the dimensions are equal. Later on, this function was used to plot the impulse response and transfer function for the filter, demonstrating its flexibility. Both the establish_figure and plot_data function greatly improved the organization and readability of the code by reducing the repetitive plotting calls and instead standardizing it in a callable function. The use of dictionaries in this program also adds to the flexibility, for any newly added data set will automatically be included in the loops that extract the dictionary data.

Part 2: Filtering the data

We chose a band-pass filter for our ECG data, as it effectively attenuates high and low-frequency artifacts. After comparing an infinite impulse response (IIR) filter with a finite impulse response (FIR) filter, we selected the FIR filter for its stability, lack of a feedback mechanism, and lack of phase distortion, allowing us to preserve the signal shape. We also adjusted the cutoff frequencies based on the data's filtering results. The band-pass filter improved beat detection by focusing on specific frequencies, making the heartbeat peak more visible, as expected, and aiding in the detection of heart rate variability (HRV) or abnormal rhythms. The filter successfully attenuated noise, with the heartbeat peaks becoming more visible in the filtered signal, matching expected behavior.

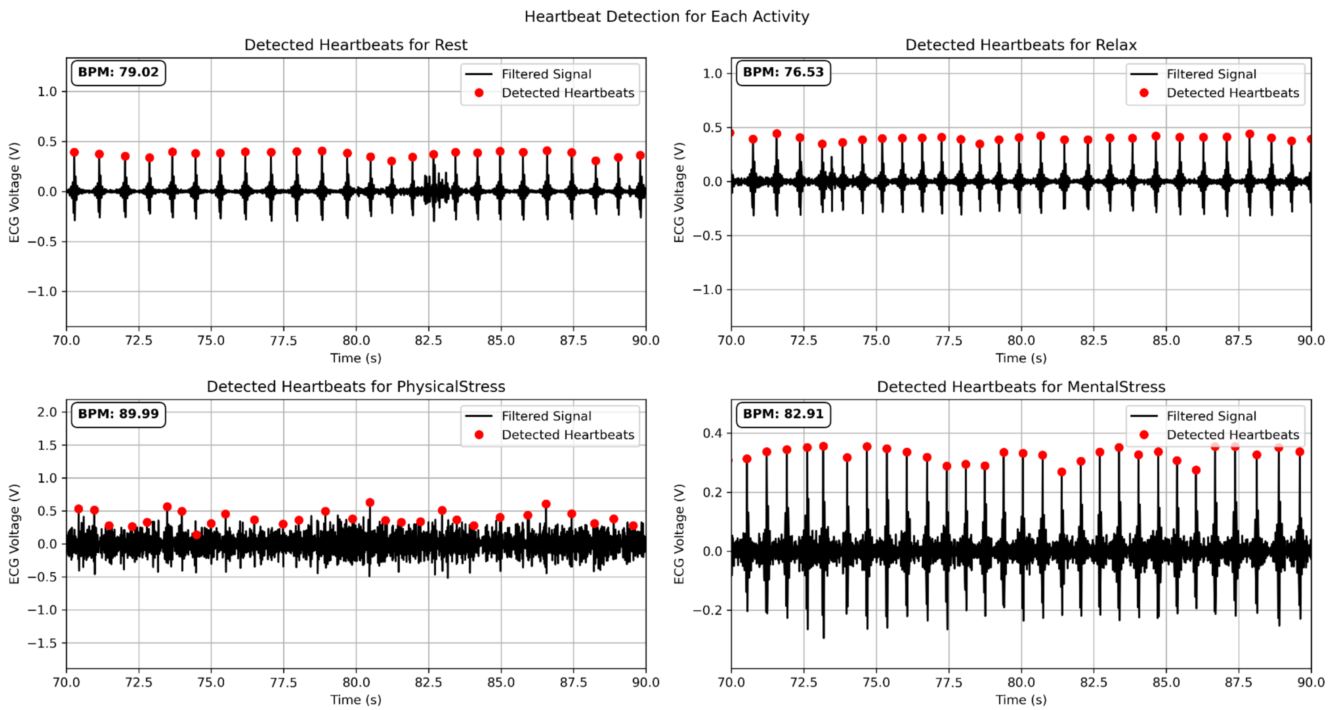
<u>Plots:</u>





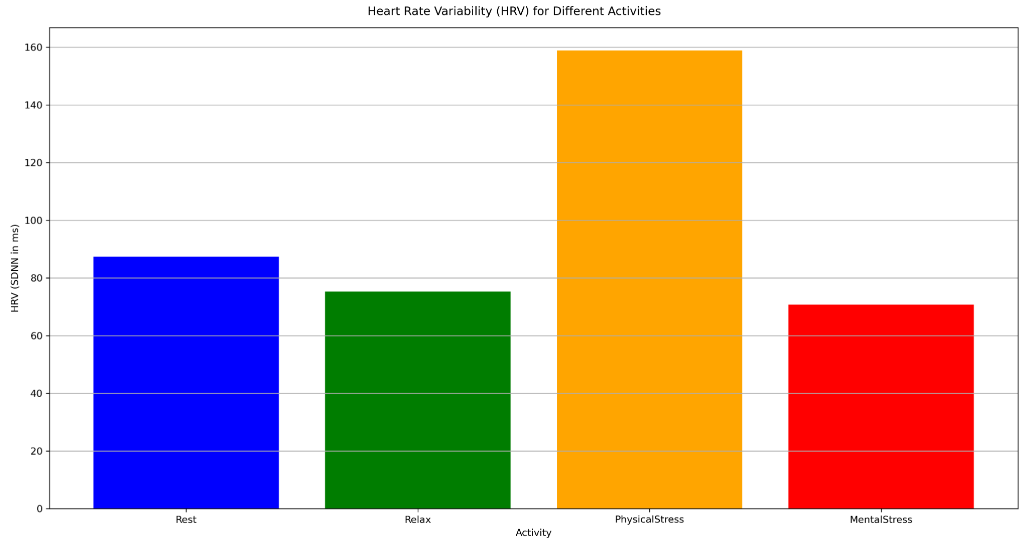
Functions:
Our first function, create_filter, creates a finite impulse response filter. It is flexible because it takes the input filter_type and allows for adjustable parameters like cutoff frequencies, which allows the user to create whatever type of filter they think is best for their data, even outside of ECG data. The second function, apply_filter, uses signal.filtfilt, which minimizes phase distortion, to filter the data. Our third function, butterworth_filter, creates an infinite impulse filter that we initially compared to the finite impulse response filter. It's flexible because it accepts low cut and high cut as parameters. It also has a customizable filter order which allows for control of the sharpness of the filter's cutoff.

Part 3: Detect Heartbeats
We utilized Scipy's built in find_peaks function to detect heartbeats. This method was chosen because it was easy to implement and because the R wave, where the beat takes place, is almost always the tallest wave. The function allowed for modifications like a minimum peak height and minimum peak distance to avoid over-detection. We found it worked well for signals with low levels of noise but signals with lots of noise and fluctuation often had beats that were missed as well as mis-marked. The plot below shows the heartbeats for the relax, mental stress, and rest activities were well detected. The physical stress activity, however, had poor detection due to the high amount of noise and motion artifacts.
Plots:



Function: Our first function, detect_heartbeats, uses scipy's find_peaks function to detect heartbeat peaks and perform basic filtering on peaks that are too low or too close together. It is flexible because it allows for easy adjusting of the minimum peak height and minimum peak distance, allowing one to adjust a parameter, observe its effect, and adjust again if needed until the detection is satisfactory. It also takes sampling frequency as an input which allows it to process signals sampled at different rates. The second function, plot_heartbeat_detection, plots heartbeats based on the times and indices where peaks were detected. This function is flexible because it allows any heartbeat detection method to be integrated into it so long as it produces times and indices where peaks are found.

Part 4: Measuring Heart Rate Variability(HRV)
According to an article on WebMD, as you become more stressed, your heart rate should rise and your HRV should go down(Spiker, 2024). This claim is somewhat corroborated by our data. For this part, we ignored the physical stress data because we felt there was too much movement during collection. Beats per minute for the activities from least to greatest is rest, relaxation, and mental stress. The HRV from greatest to least is rest, relaxation, and mental stress. Mental stress, the activity where HRV should be the lowest, followed the trend WebMD discussed but rest and relaxation swapped. For that reason, our results are inconclusive. Our belief is that this most likely happened because the tests for the activities weren't standardized. There were varying amounts of talking throughout each one which could have affected the data, as well as the previously mentioned movement.
Plots:

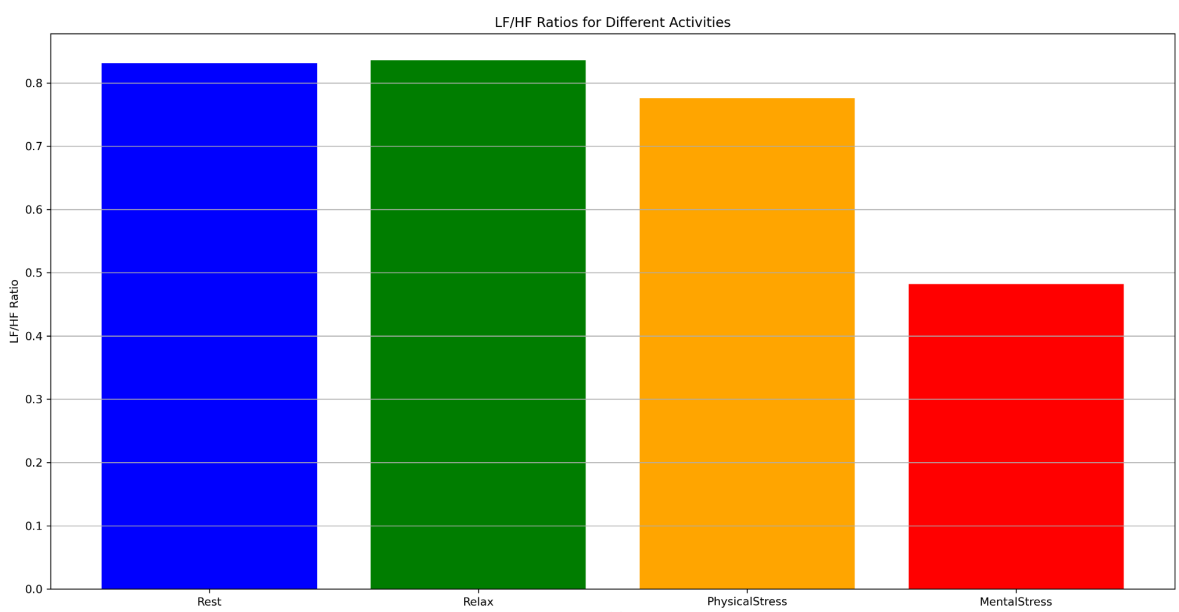


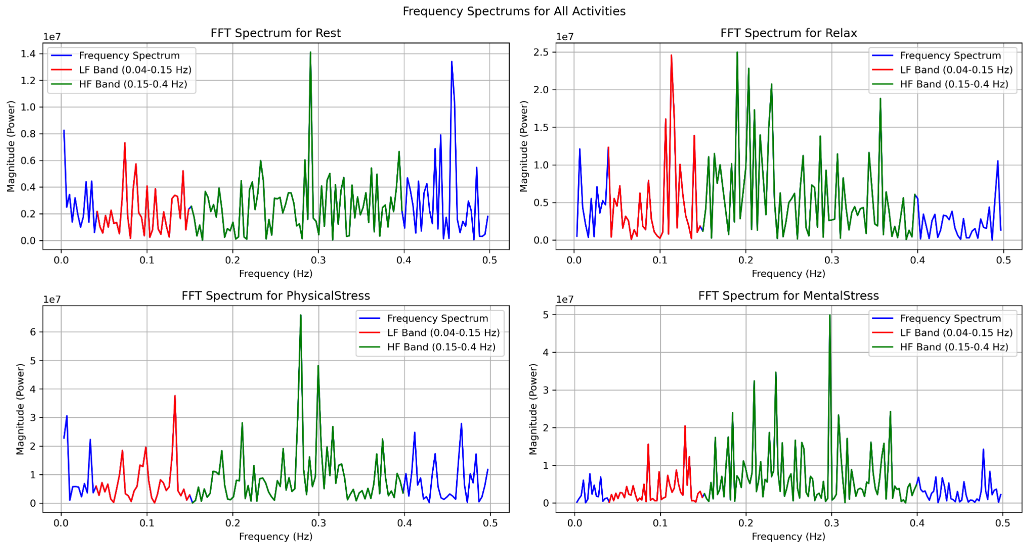
Functions: Our function for this part is interpolate_ibis. It takes heartbeat times, ibis, and the spacing of intervals as inputs. The function is flexible because it allows the user to adjust the spacing of intervals. The inputs heartbeat times and ibis are separated which means the function isn't tied to a specific data source. The function also removes the last heartbeat so it doesn't cause any errors in the data. This is because you need two heartbeats to calculate an interval.

Part 5: Get HRV Frequency Band Power

Based on the theory correlating high LF/HF ratios with high stress, we expected rest and relax to have lower LF/HF ratio values and physical and mental stress to have high LF/HF ratio values (Delaney, 2000). However, the LF/HF ratios show the reverse. Mental stress has the lowest LF/HF ratio. Because the recording duration is short, any incorrectly detected beat has a high effect on the heart rate variability and thus LF/HF ratio. For a healthy, active individual, 79 BPM as a resting heart rate is high, suggesting some error in the heartbeat detection that could contribute to later errors in the LF/HF ratio.

Plots:





Functions: Our first function, convert_to_frequency, computes the frequency domain of an ECG signal. It is flexible because it supports signals of multiple lengths and types. Our second function, get_lf_hf_ratio, calculates the LF/HF ratio based on the frequency bands for high and low frequency. It is flexible because it allows the user to specify frequency ranges for the bands. Our third function, plot_frequency_spectrum, plots the frequency spectrum for each activity with labeled LF and HF bands. It is flexible because it allows the user to customize the color and name.

Part 6: Reflect

This project set out to correlate LF/HF ratio with stress levels. A high LF/HF ratio indicates dominance of the sympathetic nervous system, or in other words, likely indicates high stress and vice versa (Delaney, 2000). As mentioned above, the physical stress data is too noisy to effectively draw conclusions from. However, heartbeat detection was quite accurate post-filtering for the other activities. The data presented above does not support the theory that a high LF/HF ratio indicates high stress, as shown by the mental stress ratio being lower than the resting and relaxing ratios. The data suggests low stress for the mental stress activity, but more likely indicates an inaccurate correlation between LF/HF ratio and stress.

To determine the LF/HF ratio, heart rate variability was used However, any small error in beat detection will have a drastic effect on the heart rate variability due to the short recording time. Unfortunately, artifacts and noise are a common cause in beats being detected incorrectly even after filtering, for these additions to the signal alter the wave pattern and add unnecessary data, in turn altering the heart rate variability and LF/HF ratio. While rest, relax, and mental stress all have good data post-filtering, even they have beat detection flaws, as suggested by the abnormally high heart rates, that affect the heart rate variability and the LF/HF ratio.

The first way to improve the data collection is to use a longer duration reading, for incorrectly detecting a few beats will not have as big of an effect on the overall heart rate variability and LF/HF ratio. Another way to improve the data collection would be a better ECG data recording setup. It was noticed that any movement of the limbs where the electrodes were attached would drastically alter the data. Furthermore, activities that inherently involved movement would introduce motion artifacts that were extremely hard to filter, as shown by the physical stress data. If accurate readings could be made while moving the electrodes, it would also allow for a greater range of activities to be performed. Lastly, a consistent method to induce mental and physical stress would benefit the analysis. In truth, it is hard to objectively compare how stressful one activity is to another. With a more concrete definition for a stressful activity and a way to record a greater variety of movement-related activities, the ECG readings would be higher quality and easier to draw heart rate variability and LF/HF ratio conclusions from.

References:

Delaney, J. P. A., & Brodie, D. A. (2000). Effects of Short-Term Psychological Stress on the Time and Frequency Domains of Heart-Rate Variability. Perceptual and Motor Skills, 91(2), 515-524. https://doi.org/10.2466/pms.2000.91.2.515

T. Spiker, “Make Heart Rate Variability Your Secret Anti-Stress Weapon,” *WebMD*, Jan. 04, 2024. Available: https://www.webmd.com/balance/stress-management/news/20240104/heart-rate-variability-anti-stress-weapon