EGR 635 Final Project:
Removal of ECG From Contaminated EMG Data

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Abstract

This project details the creation of an algorithm designed in MATLAB to efficiently eliminate electrocardiogram (ECG) interference from electromyogram (EMG) signals. Data collection involved the use of Myoware2.0 EMG sensors paired with a Teensy4.1 microcontroller and the WizFi360 wireless module. The process included meticulous skin preparation and sensor placement before recording contaminated EMG data from the Rectus Abdominus.

The algorithm filtered the data selectively using the wavelet transform. Thresholding windowed segments and a simple voting system helped to remove the ECG while preserving the EMG. Additionally, a basic EMG activation algorithm was used to apply different ECG filtering during relaxation and contraction.

The algorithm performance was good, but a variety of factors such as a different test subject, different sensor placement, or a different sampling frequency could affect the tuned parameters of the algorithm and thus its ability to remove ECG. In the future, a more diverse data set would be required to generalize the algorithm.

Introduction

An electromyogram (EMG) captures the electrical signals generated within muscles when they are contracting. EMG signals are commonly analyzed to evaluate gate, muscle activation levels, muscle interplay, power spectra changes with fatigue, and more. EMG is most commonly recorded on the surface of the skin above the muscle of interest, but can also be performed using a fine wire placed under the skin into the muscle.

An essential variable for quantifying the EMG signal is power, often obtained through non-linear wavelet transform methods (von Tscharner, 2000). However, challenges like power line interference, electronic noise, and movement artifacts frequently co-occur during EMG measurements. Advanced techniques such as wavelet analysis or independent component analysis are available to mitigate these unwanted signals (Ren et al., 2006).

EMG recordings from certain body areas, especially the trunk, are prone to contamination by the electrical activity of the heart muscle (ECG) due to their proximity to the heart. The ECG signal can significantly contribute to EMG signal power, necessitating the suppression or separation of the ECG signal during analysis.

Two common methods of dealing with this are to remove the periods where the QRS complex is present or to apply a high-pass Butterworth filter. Both of these methods offer potentially simple and effective removal of ECG, however, they also result in the loss of the original EMG signal.

Adhering to the Standards for Reporting EMG Data of the Journal of Electromyography and Kinesiology, EMG should be recorded within a frequency band of 10 to 350 Hz, and filtering in the 50–350 Hz range is not recommended. Ideally, the removal of contaminating ECG from recorded EMG should preserve the low-frequency components of the EMG signal whenever possible (Marletti, 2016).

For this project, data was recorded that would purposefully be contaminated with ECG, and then a method of removing ECG from EMG was designed. The new method combined ideas from the previous simple methods to filter more effectively while preserving more of the original signal. The algorithm programmatically found the QRS complexes in the wavelet transform, then the data was filtered using a basic voting system, which helped preserve the original signal.

MATERIALS

Table 1: Materials & Software

Item Name	Description
Teensy4.1	ARM Microcontroller
WizFi360	WiFi enabled module with UART/SPI
Myoware2.0 Muscle Sensor	EMG Sensor
MQTT	Wireless communication protocol used
MATLAB	Used for the data analysis

Methods

The data used for this project were collected using Myoware2.0 EMG sensors. These pre-amplified EMG sensors had a bandpass filter from 21-498Hz to prevent aliasing and low-frequency oscillations. Additionally, these sensors have a 140dB common mode rejection ratio (CMRR). The sensor offered a raw, rectified, and envelope output; for this research, the raw output was used.

The Myoware2.0 sensor was paired with a Teensy4.1 microcontroller and the WizFi360 wireless module to record and transmit test data. Figure 1 shows the high-level schematic for the system.

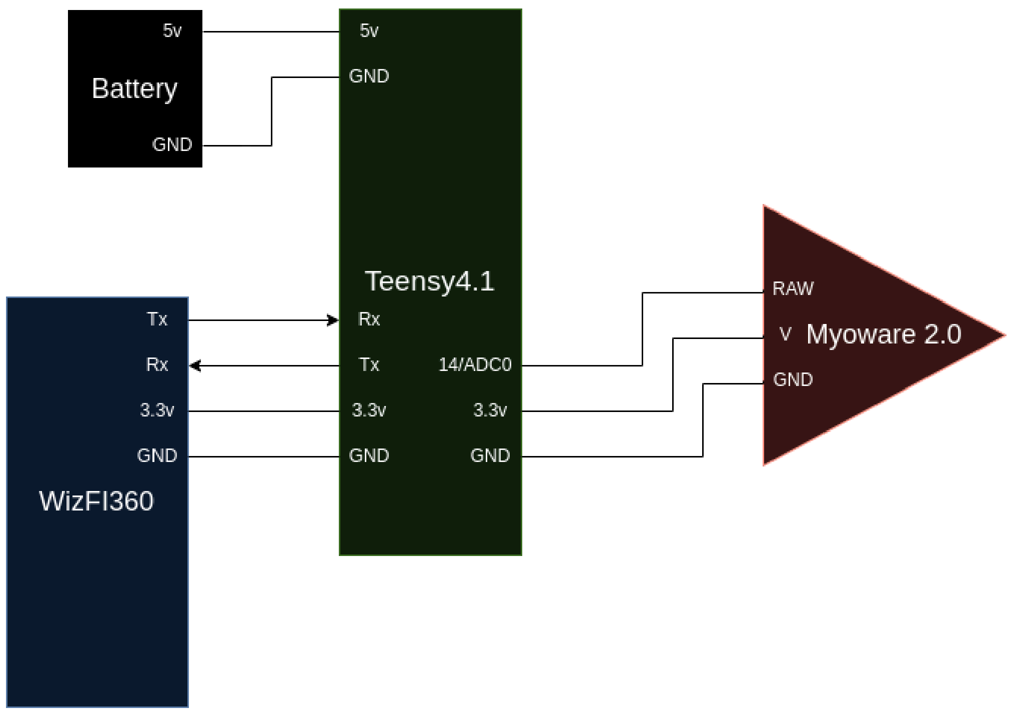

Figure 1: High-Level Schematic

The entire system was powered with a 5V regulated battery pack that connected to the Teensy4.1. The Teensy then powered the WizFi360 module and the Myoware sensor with its 3.3V supply pins. The raw output from the sensor was an analog voltage, ranging from 0v to V where V was the voltage supplied to the sensor (3.3-5V). The raw signal was connected to pin 14 on the Teensy, which was also multiplexed with channel 0 of the ADC. The ADC recorded samples at 1000 Hz with 10 bits of precision. The controls and test data were communicated over wifi using MQTT.

When recording EMG data, skin preparation and sensor placement are vital for reading a good signal. If the sensor placement or skin preparation is not done correctly, the signal may be weak, overly noisy, or may not read any signal at all.

To begin, the skin needed to be cleaned of dead skin cells and debris. This is often done with a rough exfoliating surface, such as a pumice stone or high grit sandpaper. The skin does not need to be exfoliated aggressively, just until the skin is a light red color. Next, an isopropyl alcohol wipe should be used to further clean the skin (Konrad, 2005). Lastly, if available a conductive gel such as EEG paste could be used, but is not necessary in many cases. After cleaning the skin, the Myoware sensor was applied.

To record an EMG signal that was contaminated with ECG, the Myoware sensor was placed at the top of the Rectus Abdominus near the heart as shown in Figure 2.

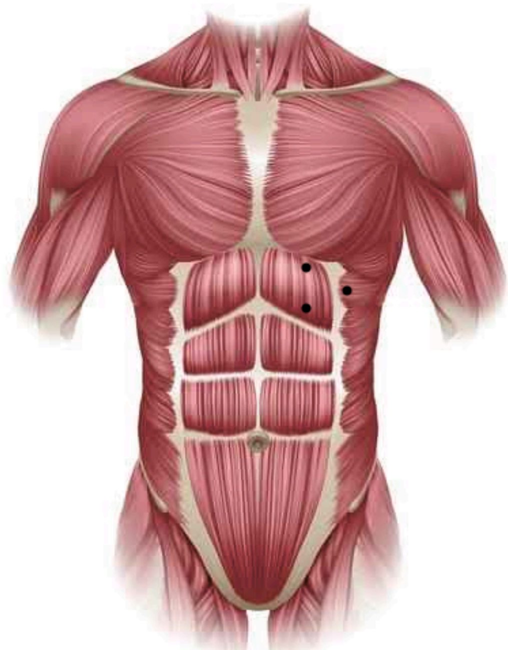

Figure 2: Sensor Placement

The two points stacked vertically represent the placement of the bipolar electrodes labeled “mid” and “end” on the Myoware sensors. The third point to the right gives the placement of the reference electrode (“ref” and ”gnd”).

After setting up the data recording system and placing the sensor, 4 tests were performed. First, a test for 5 seconds was performed where no contraction was performed. This was done to get a baseline of the ECG activity. Next, another two tests were performed where there was intermittent contraction. Lastly, some exercise was performed to elevate the heart rate and a final test was performed with intermittent contraction.

After recording the EMG data contaminated with ECG, MATLAB code was created to remove the ECG. The first step of the code was to load the data in and perform a zero mean and normalization. The data was normalized to be between -1 and 1 volts. After preparing the data, MATLAB's continuous wavelet transform (cwt) function was used to compute the wavelet transform. When examining the plot of the wavelet transform, it was noted that the QRS complex has a pyramid shape in the wavelet transform. So, it was decided that the algorithm would work by targeting these pyramid shapes for filtering. Figure 3 shows an example of the ECG wavelet transform.

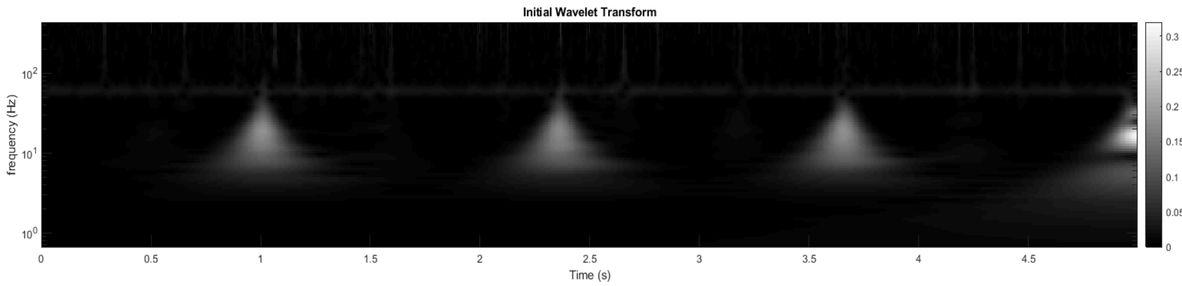

Figure 3: ECG Wavelet Transform

The code began by using a vertical window that went from a low frequency limit to a high frequency limit and averaging the pixels to determine if it was part of the pyramid. The algorithm would perform operations on one column and then move to the next. This method worked but would include much of the EMG signal in the filtered region as well. It also failed to include the edges of the pyramid. To improve upon this, the single vertical window was modified to be a series of smaller windows from the lower to upper frequency limit. This improved the algorithm's ability to capture the QRS complexes more finely but led to islands of filtering inside the EMG signal as well. To remove these islands of unwanted filtering, a basic voting system was implemented.

The voting system worked by increasing the vote count whenever a window was not determined to be part of the pyramid. Since the windows started at the base and ended at the peak, a large vote indicated that the current window was not likely part of the QRS complex. This system helped eliminate islands of filtering since filtered sections now required filtered sections underneath them. This algorithm worked fairly well, but would still at times filter out the EMG signal by extending too far into the EMG frequencies.

To fix this, a basic EMG activity detection algorithm was created so that the filtering during contraction could be different than during relaxation. During relaxation, the filtering frequency would go high to more fully eliminate the ECG signal. However, during activation, the EMG and ECG signals occupied some of the same frequencies, so the filtering would end at a lower frequency to preserve the EMG. The activity detection worked by averaging all of the pixels above the upper-frequency limit of the filter for 9 samples prior and 10 samples after to create an Nx40 matrix. Making the average include 40 samples in time had the effect of smoothing the result which in turn made selecting a threshold easier.

Algorithm performance was analyzed by visually inspecting the time domain results, but more importantly, inspecting the original and filtered wavelet transforms to see what was being selected for filtering. In the end, the high and low frequencies were selected to be 2Hz and 40Hz. The upper limit of 40Hz helped eliminate the majority of the ECG signal while also not filtering important EMG components if the algorithm made a mistake.

Results

The results comprised a comparison between the original and filtered signals. The time domain and wavelet transforms were compared visually. Below are the final results for the four trials that were run, starting with the baseline ECG in Figure 4.

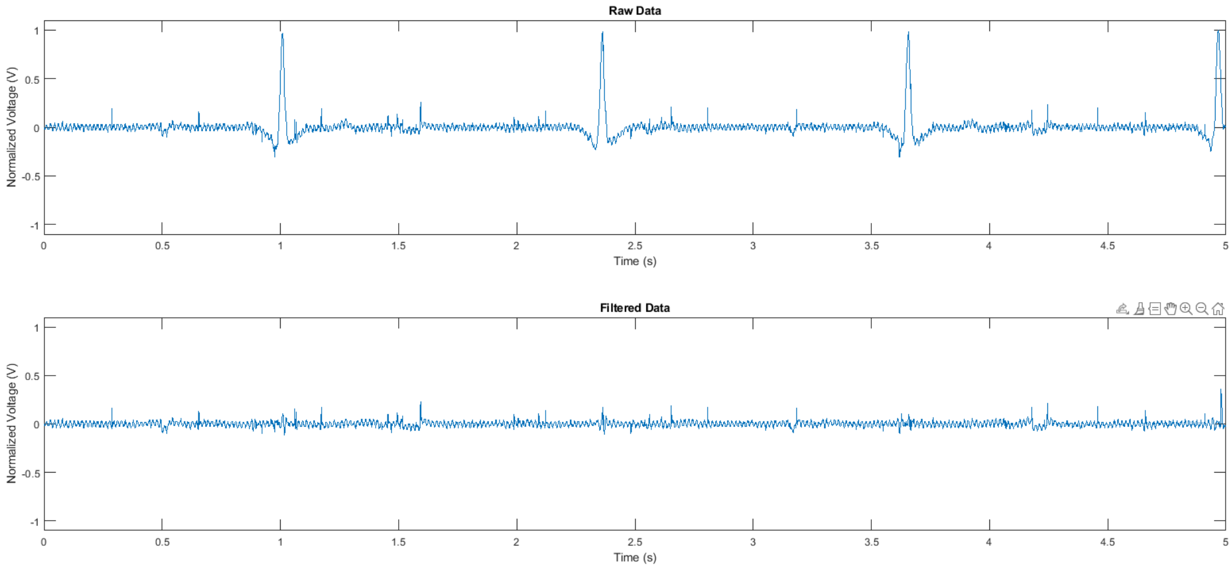

Figure 4: Original and Filtered ECG Baseline

Figure 4 shows the original data recording on the top and the filtered signal on the bottom. Notice that the original signal has noise and QRS complexes, and in the filtered signal only the noise remains. The filtering was targeted at the QRS complexes and not general filtering, so the 60Hz and higher frequency noise remained.

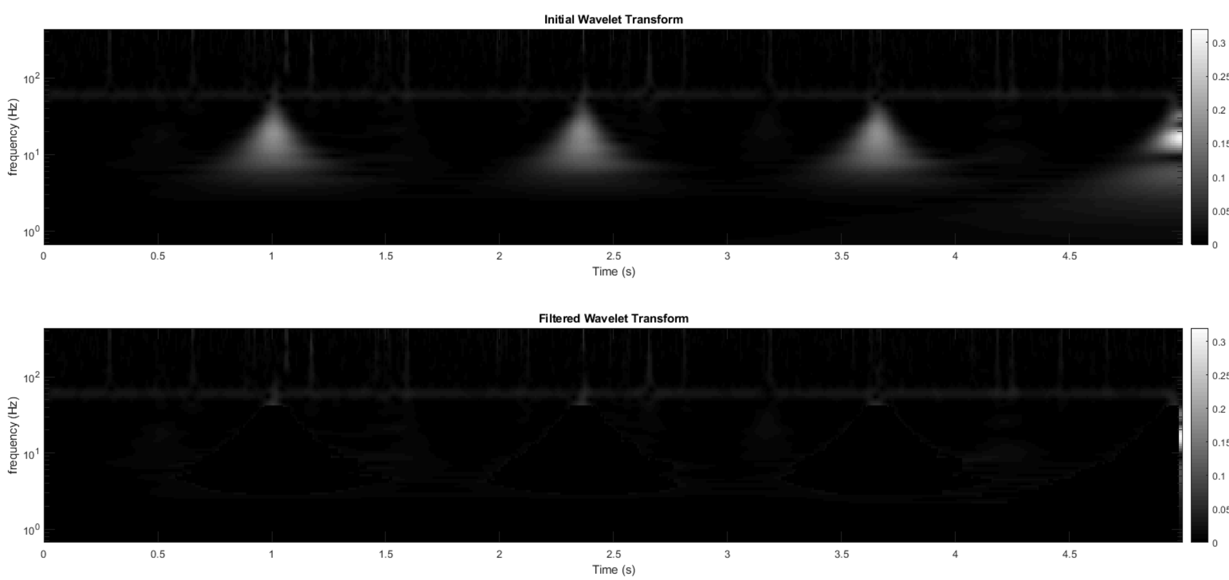

Figure 5: Original and Filtered Wavelet Transform of ECG Baseline

Figure 5 shows how the data signal was filtered. On the top is the original signals wavelet transform, and on the bottom is the filtered wavelet transform. Note that there is 60Hz noise present throughout. The filtered wavelet transform was inverted to get the filtered time domain signal.

Now, similarly to Figures 4 and 5, the next pairs of figures show the comparisons for the three main tests. The first two tests were recorded during a resting heart rate and the third test was recorded with an elevated heart rate.

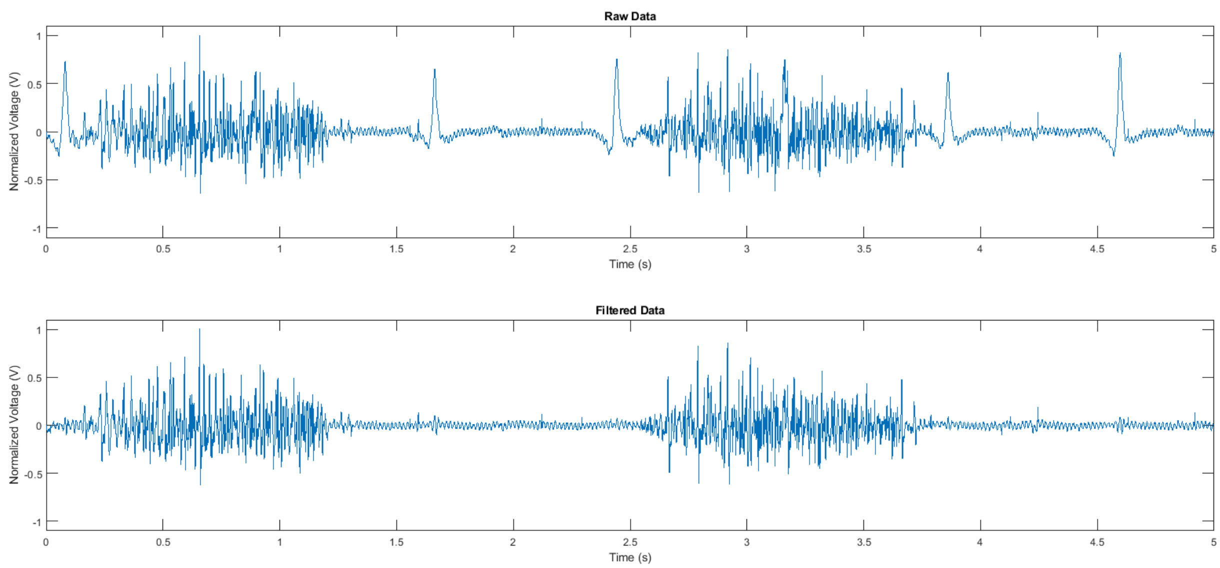

Figure 6: Original and Filtered EMG Test 1

Figure 6 shows the original EMG signal on the top and the filtered signal on the bottom. This test was a 5-second trial at resting heart rate.

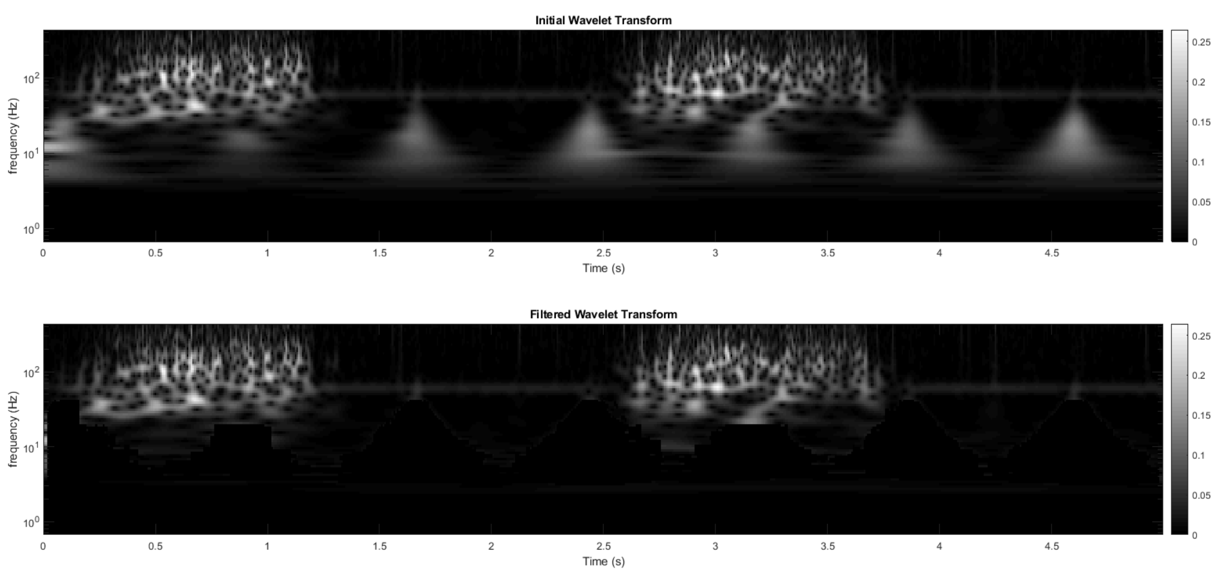

Figure 7: Original and Filtered Wavelet Transform of EMG Test 1

Figure 7 shows the original and filtered wavelet transforms. Note that the same pyramid shapes and 60Hz noise appear in the test as in the ECG baseline, so the remaining area of interest is the desired signal.

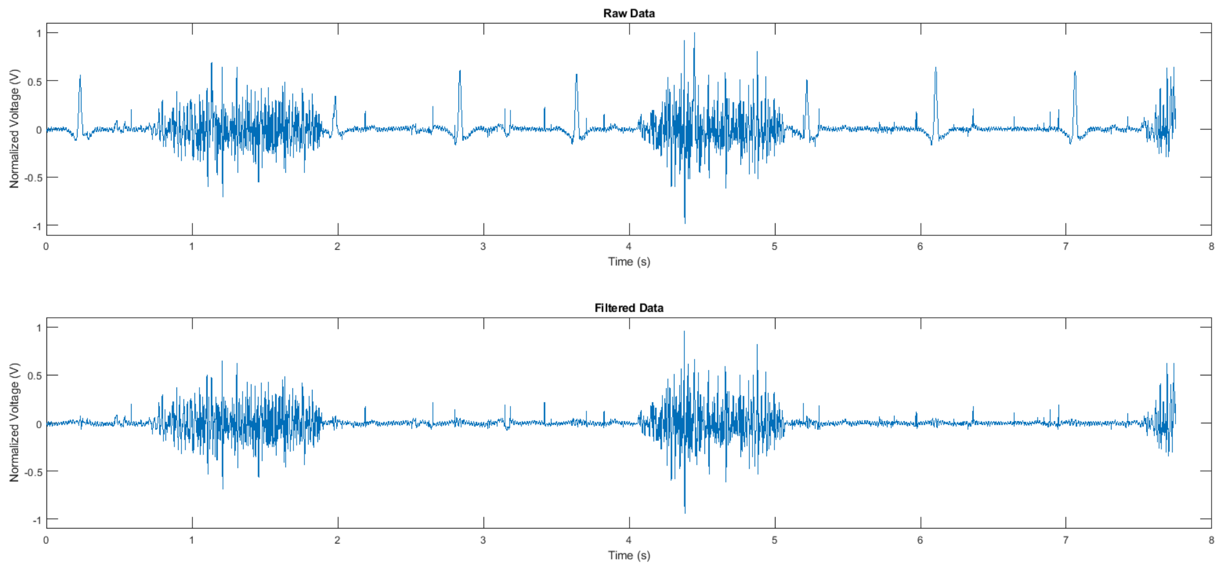

Figure 8: Original and Filtered EMG Test 2

Figure 8 shows the original EMG signal on the top and the filtered signal on the bottom. This test was a 7.5-second long trial at resting heart rate.

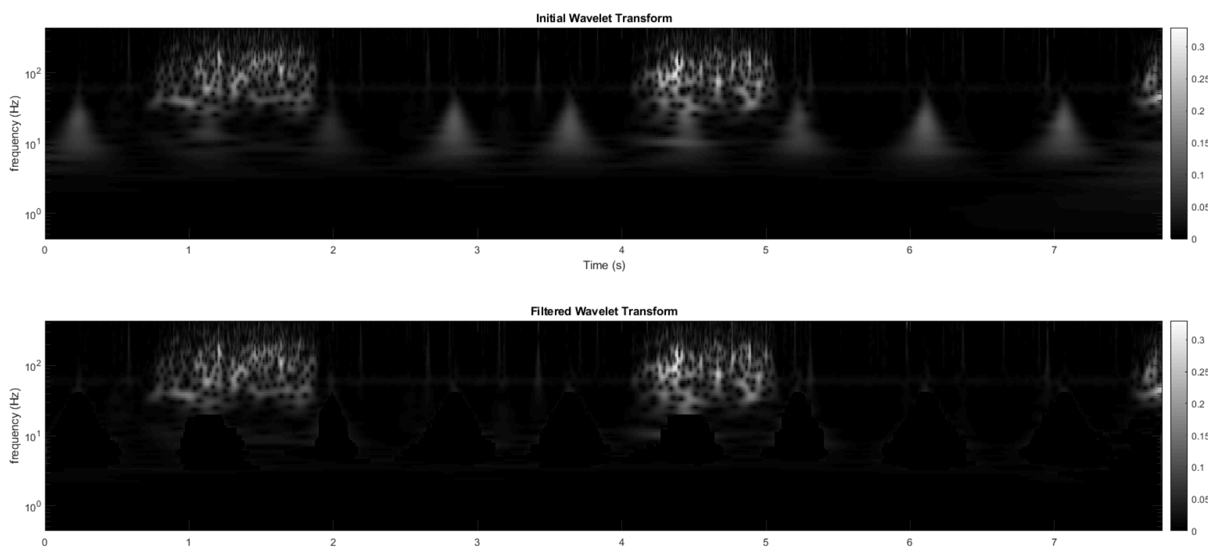

Figure 9: Original and Filtered Wavelet Transform of EMG Test 2

Figure 9 shows the original and filtered wavelet transforms. Note that the filtering of QRS complexes outside of the EMG activation reaches a higher frequency than filtering during EMG activation.

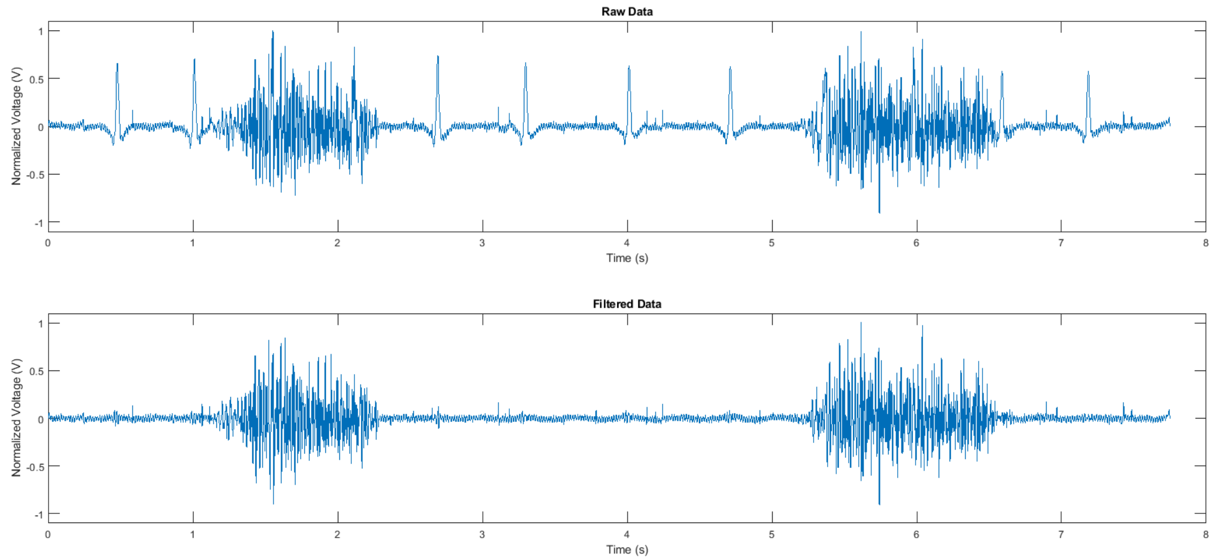

Figure 10: Original and Filtered EMG Test 3

For the last test, Figure 10 shows the original and filtered data from the third test where exercise was performed prior, elevating the heart rate.

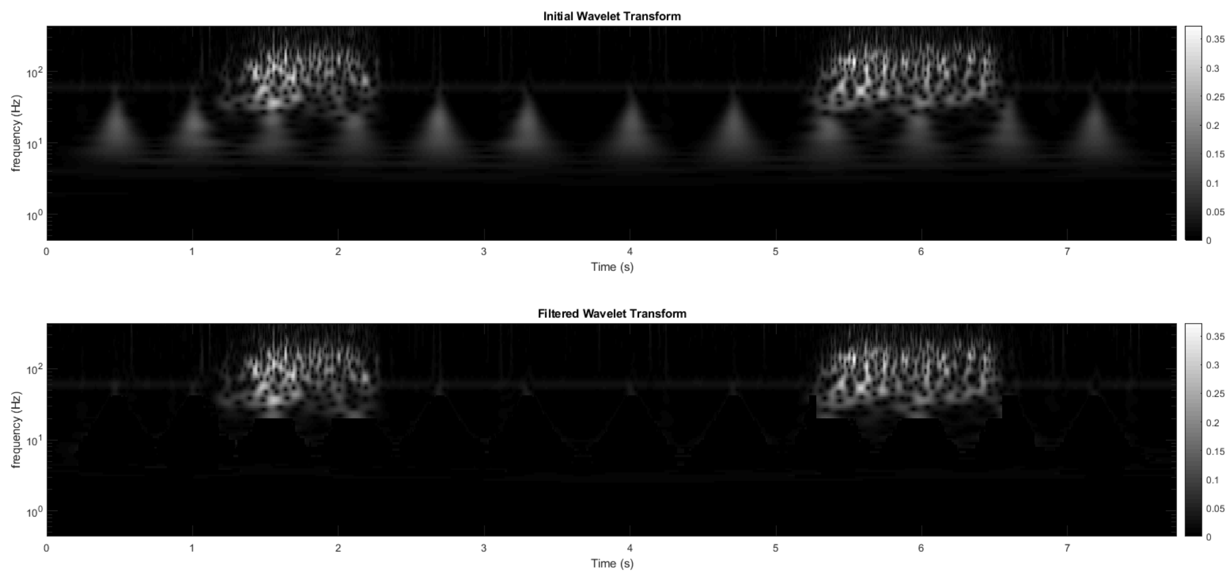

Figure 11: Original and Filtered Wavelet Transform of EMG Test 3

Figure 11 shows the original and filtered wavelet transforms. Note that the filtering of QRS complexes during the second activation filters around the EMG activation while trying to include as much of the QRS complex as possible.

Lastly the power spectrum for the raw and filtered data was calculated using Welch's Periodogram. Figure 12 shows the raw data power spectrum on top and the filtered data's power spectrum on the bottom.

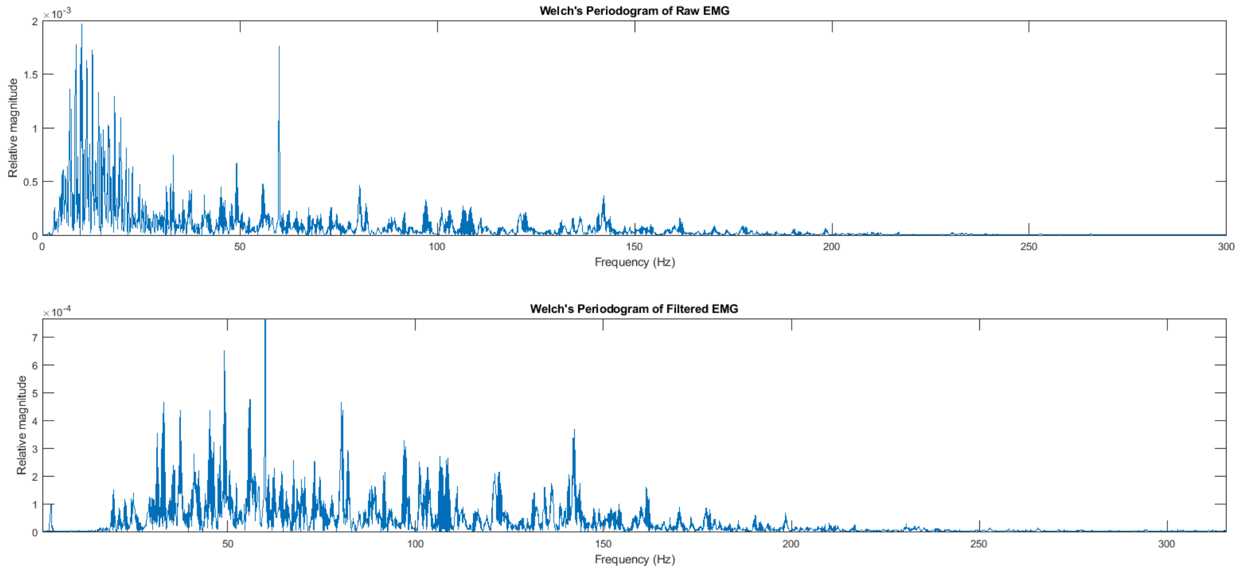

Figure 12: Raw and Filtered Data Power Spectra

It is important to note that both the raw and filtered data have large spikes around 60Hz due to the power mains. Since the relative magnitudes of the EMG were much smaller than the 60Hz noise, the bottom plot has been zoomed in to focus on EMG's contribution to the power spectrum.

Conclusion

When recording any biological signal, there is always noise and or artifacts that may interfere with the analysis of the data. Some of these sources can be eliminated, for example, better protection from power mains interference will reduce 60Hz noise; whereas other sources such as the ECG signal present on EMG recordings may be inevitable. In these circumstances, there must be options to digitally remove the ECG contamination from EMG without destroying the original EMG signal. This is exactly the case when recoding EMG signals from muscles on the upper trunk which are closer to the heart.

The algorithm developed here did a good job of removing the ECG signal from the baseline test (Figures 4 & 5), leaving only variations on the same order of magnitude as the 60Hz noise. In the other test, the algorithm performed similarly for QRS complexes that occurred during muscle relaxation. The performance during muscle activation was also fairly good, as is visible in Figures 7, 9, and 11 where the filter was applied to the pyramid shape but not the EMG activity. In Figure 11 it can be seen that when EMG activation was detected at the start and end of the second contraction, the filtering height changed to preserve the EMG.

The algorithm was very good at removing ECG content but had to be carefully tuned to avoid removing excessive amounts of EMG content. The main weakness of the algorithm is that it is not fully adaptable, meaning if data were recorded from a different individual, on a different muscle, or at a different sampling frequency, the algorithm's performance could vary. Further tests with a more broad data set are required to generalize the algorithm.

Acknowledgments

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