**Midterm Exam: EMG & ECG**

Roberto Melendez, Christopher Felix, Juliana Facchini

*Florida International University, Biomedical Engineering Department, 10555 W Flagler St, Miami, FL 33174*

1. Introduction

Electrocardiograms (ECG) and electromyographs (EMG) are fundamental diagnostic tools used to assess electrical activity in the human body. An ECG records the electrical signals generated by the heart, providing insight into cardiac function, while an EMG measures the electrical activity of muscles, aiding in the evaluation of neuromuscular health. Despite their varying purposes, procedures, waveforms, and interpretations, they are both invaluable and integral tools for evaluating cardiovascular and neuromuscular health.

This experiment aims to employ EMG and ECG sensors to acquire muscle and heart signals, process the data using MATLAB, and analyze the differences between EMG and ECG waveforms through various signal processing techniques. The study involves real-time data acquisition, filtering, and feature extraction to enhance signal quality and facilitate interpretation.

Key concepts:

**Signal Processing**: The analysis, manipulation, and interpretation of electrical signals to extract meaningful information or improve their quality.

**Filtering**: The application of signal processing techniques to remove noise and enhance data accuracy.

**Electrodes**: A device that carries electrical signals from muscles, organs, and other parts of the body to recording devices.

**Electrical activity**: The measurement of electrical properties of cells and tissues.

2. Methods and Materials

**Materials**:

* MP41 Data Acquisition Kit
* 40EL Electrode Lead Set
* Electrodes
* MATLAB with Signal Processing toolbox
* Biopac Software

**Procedure**:

1. **Hardware Setup**: The 40EL Electrode Lead Set was connected to the MP41 Data Acquisition Kit. The electrodes were attached to the subject’s skin at predefined locations to ensure accurate EMG and ECG recordings.

2. **Data Collection**:

* EMG Recording: The subject remained seated at rest for one minute, followed by muscle contractions performed in 10-second intervals for one minute.
* ECG Recording: The subject underwent the following conditions in sequence:
  + Supine rest for 20 seconds.
  + Seated rest for 20 seconds.
  + Deep breathing for 20 seconds.
  + Muscle contractions for 60 seconds, divided into 20-second intervals.
* Data from both the EMG and ECG recordings were saved into an Excel spreadsheet for further analysis.

3. **Code Implementation**: A MATLAB script was developed to:

* Data extraction and visualization: Import, read, and plot the EMG and ECG signals from the Excel file.
* Noise reduction: Create various filters to improve signal clarity.
* EMG Computation: Compute the root mean square and mean absolute value of each 10 second contraction from the EMG readings.
* ECG Computation: The cardiac cycle, P-R interval, QT interval, and R-R interval were identified and analyzed for each condition.

3. Results

A diagram of a sound wave

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Figure 1- EMG Raw, Filtered, and Cleaned Signal

Figure 1 displays the raw, filtered, and cleaned EMG signal. In the raw EMG signal, particularly when the subject was at rest for the initial minute, the signal should ideally be low; however, significant noise is present. To mitigate this, a band-pass filter with a frequency range of 0-500 Hz was applied, removing noise outside this spectrum. Further refinement was achieved by incorporating a combination of band-pass, notch, and high-pass filters, which eliminated additional background noise, including powerline interference and baseline wander. The cleaned EMG signal more accurately represents true muscle activity, providing a clearer distinction between contraction and relaxation periods.

A diagram of ecg signal

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Figure 2- ECG Raw, Filtered, and Cleaned Signal

Similar to the EMG signal, the raw ECG signal exhibited inconsistencies, including various signal jumps that could interfere with accurate waveform analysis. Figure 2 illustrates the effectiveness of applying a band-pass filter, which isolated the electrical activity relevant to the subject's physiological processes. The cleaned signal further employed notch and high-pass filters in conjunction with the band-pass filter to eliminate residual noise and baseline drift, resulting in a signal that closely aligns with expected ECG waveforms.

A close-up of a graph

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Figure 3- Normalization of ECG & EMG Signals

Following the filtering process, both signals underwent normalization to enable direct comparison. Figure 3 demonstrates the effects of this process, where inconsistencies and redundancies in the data were minimized, allowing for a more standardized representation. The ECG signal appears significantly cleaner and aligns closely with the expected output due to its collection in a controlled indoor environment. Conversely, the EMG signal, recorded in a less controlled setting, retained minor inconsistencies, reflecting the inherent challenges of real-world signal acquisition.

|  |  |  |
| --- | --- | --- |
| Clench # | Root Mean Square | Mean Absolute Value |
| 1 | 0.13368 | 0.1033 |
| 2 | 0.07332 | 0.057936 |
| 3 | 0.18152 | 0.14049 |

Figure 4- Table 1.1

Figure 4 presents Table 1.1, which quantifies muscle effort during EMG data collection through root mean square (RMS) and mean absolute value (MAV) calculations. These metrics provide insight into muscle activation levels during each clench. Higher RMS and MAV values indicate stronger muscle contractions, as observed in Clench 3, which exhibits the highest values. Conversely, Clench 2 shows a lower intensity, suggesting a weaker contraction.

A graph of a graph showing a wave

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Figure 5- R-peaks in ECG Signal

Figure 5 highlights the R-peaks in the ECG signal, marked by red hollow circles. R-peaks represent the positive peaks in the electrical wave cycle, corresponding to ventricular contractions of the heart. These peaks are critical for heart rate and rhythm analysis. During the one-minute muscle contraction phase, an increase in R-peak frequency is observed, indicating a physiological response to muscle exertion. The increased oxygen demand of active muscles led to a rise in heart rate, demonstrating the expected correlation between physical exertion and cardiac activity.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Recording: Condition | Cardiac Cycle  1 | Cardiac Cycle  2 | Cardiac Cycle  3 | Mean |
| Supine | 0.875 | 18.929 | N/A | 9.902 |
| Seated | 0.927 | 1.101 | 0.851 | 5.3587 |
| Start of inhale | 2.618 | 3.941 | 2.447 | 3.002 |
| Start of exhale | 1.085 | 1.924 | 0.758 | 1.5462 |
| During muscle contractions | 1.562 | 3.687 | 0.823 | 1.7665 |

Figure 6- Table 2.1

Figure 6 presents Table 2.1, which documents three recorded cardiac cycles under various ECG conditions, alongside their mean values. The data reveal notable differences in cardiac cycle durations based on body position, breathing phases, and muscle exertion levels.

* **Supine Position:** Exhibited the longest cardiac cycle duration, averaging 9.902 seconds, due to decreased sympathetic nervous system activity in a relaxed state.
* **Seated Position:** Demonstrated a shorter cardiac cycle duration (mean: 5.3587 seconds), attributed to a slight increase in heart rate as a response to posture change.
* **Respiratory Influence:** Deep inhalation and exhalation phases affected cycle duration, with inhalation showing an average of 3.002 seconds and exhalation at 1.5462 seconds, consistent with the effects of respiratory sinus arrhythmia.
* **Muscle Contractions:** The shortest mean cardiac cycle duration (1.7665 seconds) was observed during muscle contractions, highlighting the expected increase in heart rate due to increased metabolic demand.

4. Discussion

The results of this experiment aligned well with physiological expectations, despite environmental factors and equipment constraints. The data illustrated clear trends between rest and physical activity, where EMG and ECG waveforms responded accordingly to muscular contractions and changes in heart rate. Effective signal processing techniques significantly enhanced the clarity of the recorded data, allowing for improved visualization of real-world phenomena.

**Challenges and Solutions**:

1. Code Execution Difficulties: There were errors in the MATLAB for-loop initially which prevented the generation of table 1.1 in figure 4. Debugging efforts involved revising loop structures and ensuring correct indexing for clench segmentation. Moreover, early iterations of table 2.1’s script displayed only a single cardiac cycle as opposed to the three per condition. The solution involved implementing a custom function (get\_cycles) to systematically extract and analyze three cycles for each ECG condition.
2. Biopac Software Learning Curve: As first-time users of Biopac, our group faced challenges when exporting signal data to Excel. The initial attempts resulted in single-point extractions rather than full waveforms. By extensively consulting the user manual and modifying export settings, we successfully retrieved the complete datasets necessary for analysis.

Despite the obstacles encountered, this experiment provided valuable hands-on experience in biomedical signal processing, reinforcing concepts applicable to real-world medical diagnostics. The ability to filter and analyze physiological signals is fundamental in fields like cardiology, where accurate data interpretation can inform critical health decisions.

In conclusion, the successful application of signal processing techniques, feature extraction, and normalization allowed for the accurate characterization of EMG and ECG signals. Future improvements could include refining electrode placement, optimizing filter parameters, and automating data extraction processes for increased efficiency and precision.

5. References

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