Final Report: Electrocardiogram Sonification

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I. OVERVIEW

This report details the completion of my senior capstone project as described in SDD v1.0a.

II. PROGRESS SINCE WINTER 2022 QUARTER REPORT

Preamble from a note made after Winter 2022 Quarter Report:
This project has reached a crossroads. Initially, I had proposed using `C++` to build a biosignal sonification tool which utilized `ChucK` and compiled down to an executable which may be employed on a microcomputer. This was done with the interest in algorithm speed, versatility, and a cross-platform approach in mind. However, due to the lack of adequete libraries for processing and analysis of electrocardiogram data (ECG) in `C++` and the ease of ECG processing, analysis, and annotation in `Python`, this project will now need to move to a repository based off `Python`. After sufficient development in `Python`, it will be possible to export the sonification algorithm to `C++`, but `Python` will used for initial development. In Winter 2022 Quarter Report I detailed a plan to transition from the amplitude analysis program written to an algorithm incorporating heart rate variability (HRV), live data acquisition, pulse oximetrey, and blood pressure readings. However, after spending sufficient time on ECG HRV analysis, I decided to approach this project with depth in heart data as opposed to breadth across numerous physiological parameters. In addition to analyzing raw ECG data to calculate HRV and heart rate (HR), I will use probability and statistics to add additional measures of heart health. Using information theory and Shannon Entropy, I will calculate the information content of an observed HRV value relative to a mean to measure how *surprising* observed HRV values are. Since the milestones summarized in Winter 2022 Quarter Report, I have accomplished the following:

1. Development of ECG processing and analysis software using `Python`.
2. Development of an electrocardiogram (ECG) sonification algorithm utilizing heart rate, heart rate variability, statistics, and information theory to represent ECG data in a musical paradigm.

III. METHODS

In this section, I will detail the methods used in the final iteration of my senior capstone project.

i. ECG Data Analysis in `Python`

The architecture of the ECG analysis pipeline in `Python` is as follows:

```
|--> Python 3
|----> heartpy: library to extract measures of HRV (RMSSD) and HR
|----> matplotlib: to plot ECG data and check HRV and HR analysis
|----> scipy: to calculate statistical distributions
|----> numpy: to randomly calculate the root note from a
              probability mass function
|----> pythonosc: open sound control (OSC) library to implement
                  an OSC client in Python to communicate with ChucK
```

`ecg_hrv.py` handles ECG data analysis and communication with `ChucK`. ECG data is read from a `.csv` file containing amplitudes over a designated sampling rate in Hz (samples per second). The `readECG()` function wraps a `heartpy` function to extract amplitudes from a `.csv` file and imports them into an array which can then be further acted upon. This raw data can be plotted to check for noise or artifacts before analyzing for HRV and HR. The ECG data is then passed to `processBySegment()` which analyzes the raw ECG data for measures of HR and HRV. This is done by first calculating the R peak – the maximum electrical voltage which appears in the QRS complex on an ECG and refers to depolarization of the right and left ventricles of the heart and contraction of the large ventricular muscles (see QRS Complex).

To identify heartbeats, a moving average is calculated using a window of 0.75 seconds on both sides of each data point. The first and last 0.75 seconds of the signal are populated with the signal's mean; no moving average is generated for these sections. Regions of interest (ROI) are marked between two points of intersection where the signal amplitude is larger than the moving average. This is much like the *Pan-Tomkins Algorithm*.

Once heartbeat peaks have been identified, HR, in beats per minute (bpm), can be calculated with the following equation

$$HR(bpm) = \frac{60}{RR(s)}$$

where 60 seconds is divided by the time between two consecutive R-peaks (RR) in seconds.

HRV is calculated as a measure of the root mean square of successive differences (RMSSD) which is the square root of the mean time between R-peaks (RR_n). RMSSD is calculated using the following equation

$$RMSSD = \sqrt{\frac{1}{n-2}\sum_{i=0}^{n-2}(RR_i - RR_{i+1})^2}$$

where n is the number of R-peaks used in analysis. HRV is an accepted and reliable means for assessing autonomic nervous system dysfunction and the heart muscle's ability to change to meet physiological demand. Average HRV for infants is 153.1 ms and decreases in age to an average of 17.9 ms after the age of 80 (van den Berg et al. 2018) A 5-minute measurement of HRV is considered methodologically adequate. Nussinovitch et al. (2011) found that RMSSD seems to be a reliable parameter for assessing HRV from ultra-short (1 minute or 10 seconds) resting electrocardiographic recordings. As such, I used a 10 second window as a processing length for `processBySegment()`. Nussinovitch et al. found that the mean HRV over a 10 second window was $\mu = 38.70$ ms with a standard deviation of $SD = 33.27$ ms. These values were used to approximate a normal distribution such that the probability of each observed HRV value could be calculated.

Lastly, the `Python` program calculated the information content of each observed HRV value to apply a metric of how *surprising* the resulting sonification should be. This value was calculated relative to the PMF of the observed HRV value in respect to a normal distribution with mean μ and standard deviation SD. The equation for the information content or *surprisal* of an event E is a function which increases as the probability $p(E)$ of an event decreases. It is calculated with the following equation

$$I(E) = \log_2 \left(\frac{1}{P(HRV = X_i)} \right)$$

and is left in terms of bits (the unit of measurement for log with a base of 2). The computed measures of HR, HRV, root note (see *Compositional Algorithm* below), CDF of HRV, and information content of the observed HRV were sent to `ChucK` over open sound control (OSC).

ii. Sonification in ChucK

The architecture of the `ChucK` program is as follows:

```
|--> ChucK
|----> oscServ(): OSC server
|----> sonify(): ECG data sonification algorithm
|----> cal_HR_octave(): calculate octave of notes
       to be played as a function of HR
|----> Synth [CLASS]: Synthesizer instrument class
|----> baseline(): construct a melody from random
                   chance as a baseline to compare the sonfication to
```

`ChucK` handled the sonification of the ECG measures using the compositional algorithm detailed below.

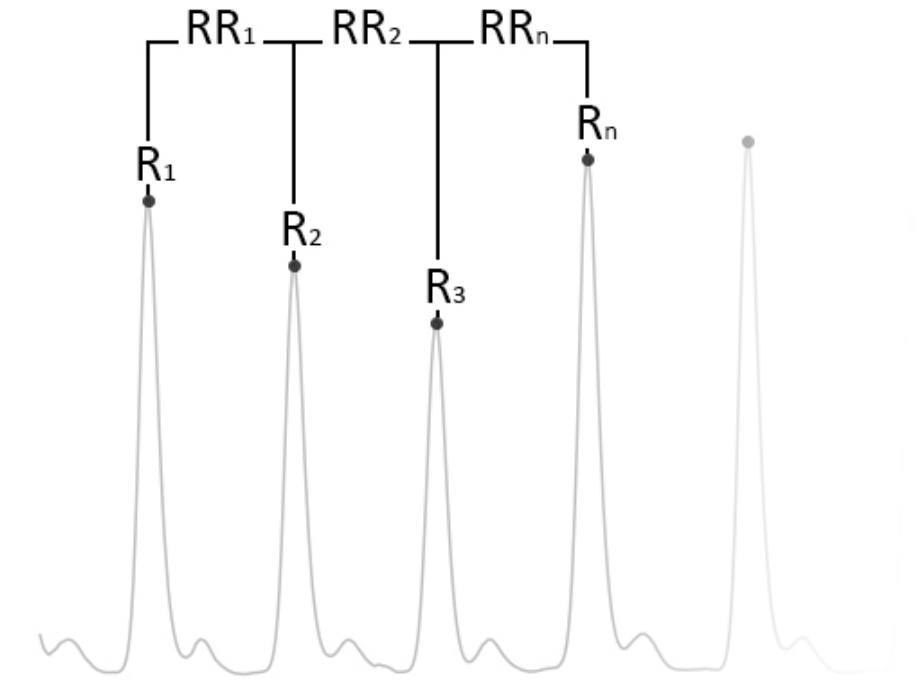

Figure 1: image of the RR interval

iii. Compositional Algorithm

Detailed here is the algorithm I developed for ECG biosignal sonification using HRV, HR, and Shannon Entropy.

```
Note, that values used for HRV or HR cutoffs of tiers are
arbitrarily chosen by preference and experience, but have
some relation to the $SD$ of each type of measure.

Python:
START
1. Calculate the RMSDD and HR of heart data in 10 second segments.
2. For each segment:
    3. Calculate the shannon entropy using the PMF of the observed
    HRV (mu = 38.7, SD = 33.27) and apply that value to the
    probability that a chord is played.
    4. Calculate the CDF of observed HRV (mu = 38.7, SD = 33.27)
    5. The root is determined by the conditions below:
```

`HRV Tiers (mu = 38.7, SD = 33.27)` [source]

```
        6. If the previous root is I (the default is I):
            7. The root is determined by the HRV PMF table below.
```

HRV Range	I	ii	iii	IV	V	vi	vii
<16.5	0.00	0.00	0.02	0.00	0.08	0.10	0.80
<22.1 && >=16.5	0.10	0.10	0.05	0.05	0.30	0.10	0.30
<27.6 && >=22.1	0.20	0.10	0.18	0.10	0.30	0.02	0.10
<38.7 && >=27.6	0.15	0.14	0.14	0.14	0.15	0.14	0.14
<49.8 && >=38.7	0.20	0.10	0.08	0.12	0.30	0.10	0.10
<55.5 && >=49.8	0.40	0.10	0.00	0.10	0.08	0.30	0.02
>=55.5	0.30	0.00	0.00	0.30	0.30	0.10	0.00

```
        8. If the previous root is ii, iii, IV, or vi:
            9. The root is determined by the HRV PMF table below.
```

HRV Range	I	ii	iii	IV	V	vi	vii
<16.5	0.00	0.20	0.30	0.08	0.02	0.10	0.30
<22.1 && >=16.5	0.00	0.30	0.30	0.00	0.05	0.05	0.30
<27.6 && >=22.1	0.10	0.30	0.08	0.05	0.12	0.05	0.30
<38.7 && >=27.6	0.10	0.04	0.00	0.05	0.26	0.30	0.25
<49.8 && >=38.7	0.10	0.16	0.04	0.15	0.30	0.15	0.10
<55.5 && >=49.8	0.10	0.05	0.00	0.10	0.40	0.15	0.20
>=55.5	0.00	0.10	0.00	0.00	0.60	0.00	0.30

```
        10. If the previous root is V or vii:
            11. The root is determined by the HRV PMF table below:
```

HRV Range	I	ii	iii	IV	V	vi	vii
<16.5	0.00	0.10	0.30	0.10	0.02	0.40	0.08
<22.1 && >=16.5	0.00	0.20	0.30	0.10	0.02	0.30	0.08
<27.6 && >=22.1	0.20	0.20	0.00	0.08	0.10	0.30	0.12
<38.7 && >=27.6	0.30	0.10	0.00	0.00	0.20	0.20	0.20
<49.8 && >=38.7	0.45	0.05	0.00	0.12	0.25	0.05	0.08
<55.5 && >=49.8	0.50	0.00	0.00	0.05	0.30	0.05	0.10
>=55.5	0.70	0.00	0.00	0.00	0.25	0.05	0.00

```
    12. Send the raw HR, raw HRV, CDF of HRV, root, and entropy
    calculation to ChucK
STOP

ChucK
START
1. For each note:
    2. The probability of a note actually being played is the
    CDF of the observed HRV.
    3. Choose the octave of the root.
        4. If HR is lower than 40 then HR is in C2 octave.
        5. If HR is between 40 and 55 then HR is in C3 octave.
        6. If HR is between 55 and 75 then HR is in C4 octave.
        7. If HR is between 75 and 90 then HR is in C5 octave.
        8. If HR is greater than 90 then HR is in C6 octave.
    9. Choose the depth of notes to be played.
        10. If HRV is 27.6 or less:
            11. If the root is vii, then the notes come from a
            diminished chord. Array of MIDI note intervals above
            a root, chosen randomly from: [0, 3, 6, 12, -6, 15].
            12. Else, the notes from from a minor chord.
                Array of MIDI note intervals above a root,
                chosen randomly from: [0, 3, 7, 12, -5, 15].
        13. Else:
            14. If the root is vii, then the notes come from a
            diminished chord. Array of MIDI note intervals above
            a root, chosen randomly from: [0, 3, 6, 12, -6, 15].
            15. Else, if the root is ii, iii, vi, then the notes
            come from a minor chord. Array of MIDI note intervals
            above a root, chosen randomly from: [0, 3, 7, 12, -5, 15]
            16. Else, the notes come from a major chord. Array of
            MIDI note intervals above a root, chosen randomly
            from: [0, 4, 7, 12, -5, 16]

    17. If the informational entropy value of the observed HRV value
    occuring is greater than 8.005 (this value is the information of
```

```
    the mean HRV value (6.382) plus the information value of the mean
    HRV plus one and a half the standard deviation of the HRV
    distribution (33.27):
        18. Play the array of notes 3 times simultaneously to create
        polyphony.
        19. Wait the duration between notes as calculated by HR.
        20. HR / 60 bpm is the time in seconds between notes.
        21. Wait 5 seconds after all notes have been played before
        exiting the function to allow
        the reverb to ring out to complete silence.
    22. Else:
        23. Play the array of notes once.
        24. Wait the duration between notes as calculated by HR.
        25. HR / 60 bpm is the time in seconds between notes.
        26. Wait 5 seconds after all notes have been played before
        exiting the function to allow
        the reverb to ring out to complete silence.
STOP
```

IV. CONCLUSION

Using this software, I have analyzed three distinct sets of ECG data which each offer a unique compositional opportunity. In this report I have included my sonification of three types of heart rhythms. Note that I have also included a baseline recording where roots, density, chords, octaves, and polyphony are generated from random chance so as to have a control to compare the ECG data against.

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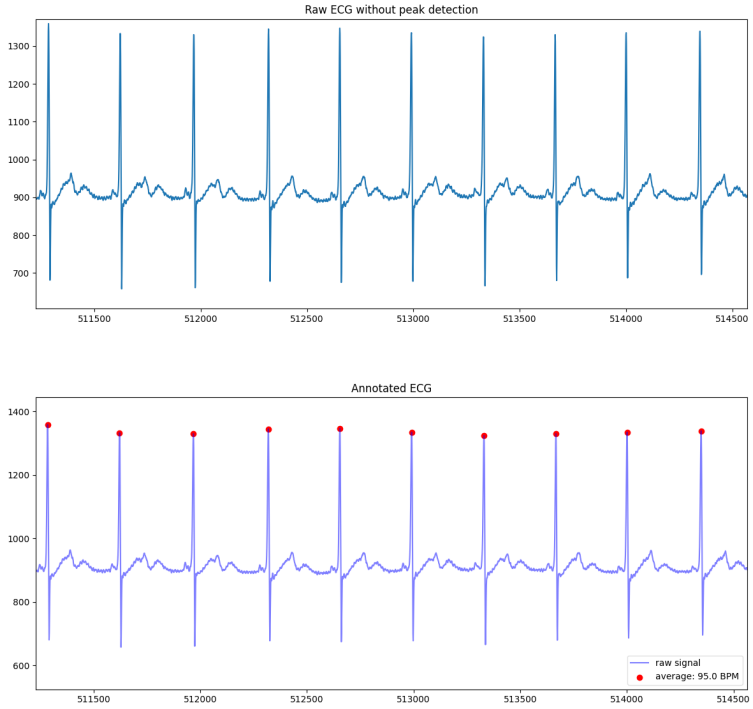
i. Normal Sinus Rhythm (NSR)

The first rhythm is normal sinus rythmn. With this data, we would expect an average HRV of μ to +2SD. The chord patterns should consist mostly of tonic and dominant sequences with deceptive candences appearing when the HRV dropped suddenly. Additionally, the texture should be dense and polyphonic with notes coming from the C5 octave predominantly.



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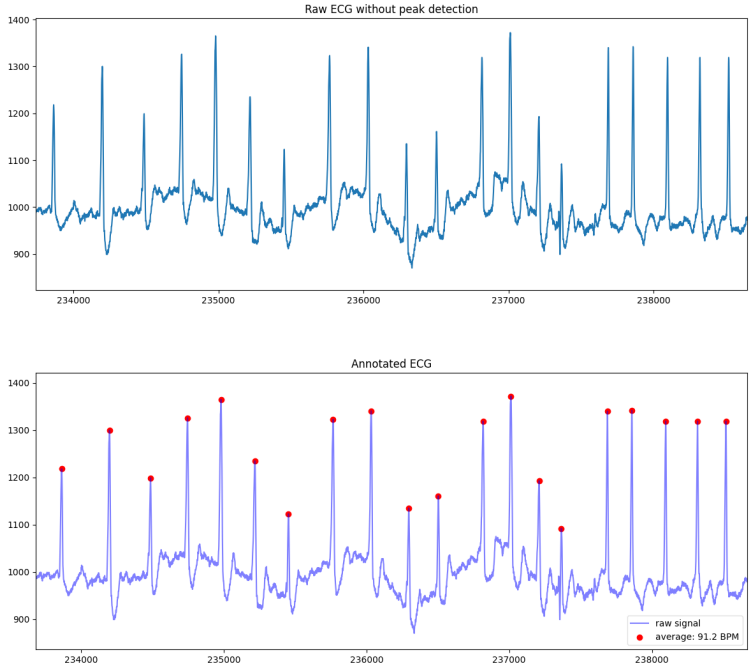
ii. Atrial Fibrillation (AFIB)

The second rhythm analyzed is atrial fibrillation. This heart rhythm typically presents as extremely fast and irregular beats from the upper chambers of the heart. In our sonification we would expect to hear a cacophony of directionless and dissonant melodies with sudden changes in density and pitch. However, what was observed in the sonification was the opposite; the melody was fast yet pleasant, with polyphony consisting mainly of tonic and dominant chords in the C5 and C6 octaves. This can be explained by the beat irregularity characteristic of AFIB. HRV is a metric based upon the ability for the heart muscle to adapt quickly to changes in demand. In other words, a high HRV is healthy and typical in athletes as the muscle is easily able to adjust to varying demands for blood. A low HRV is unhealthy and typical of sedentary habits. Therefore, it is expected for AFIB to present with high HRV (Kim et al. 2022). Compared to the sonification of NSR, AFIB has more pitch variability and a faster average length of each note played which can be explained by the exceptionally quick HR. Additionally, because each measure was irregular, the information content for observed HRV measures yielded a high amount of surprise (entropy) and thus the sonification contained large amounts of polyphony.



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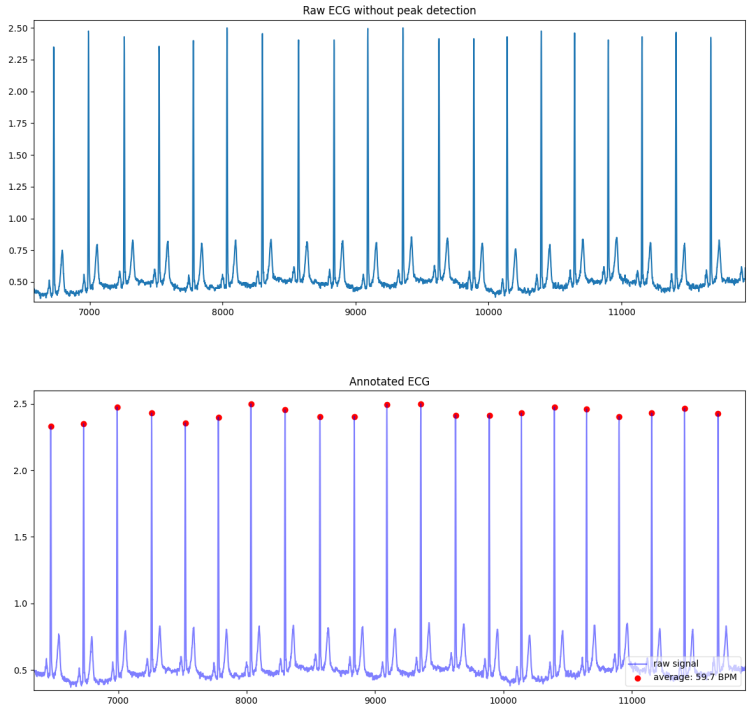
iii. Myocardial Ischemia (MI)

The last rhythm analyzed is myocardial ischemia (MI). MI occurs when blood flow to the heart is reduced, preventing the heart muscle from receiving enough oxygen. MI presents in an ECG as a flat or down-sloping ST-segment which wasn't analyzed with this algorithm. Additionally, MI typically doesn't have much effect on R-peak distance and therefore the sonification presents much like NSR, but with lower HRV and HR. Little-to-no polyphony and more subdominant and predominant chords as well as deceptive cadences can be heard. The HR didn't tend to fluctuate out of the C4 octave.



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V. LOOKING INTO THE FUTURE

Possible expansions for this project include the following:

1. Including measures of Shannon Entropy to encompass the total expected information content in an ECG recording.
2. Measuring differences in peak amplitude to gain greater insight into heart rhythms such as AFIB.
3. Embedding `Python` into `C++` to compile this program down to a cross-platform executable which may be run on a microcomputer such as the *Raspberry Pi*.
4. Live data acquisition and algorithmic composition.

ACKNOWLEDGMENTS

The following ECG datasets were used:

1. MIT-BIH Arrhythmia database DOI: 10.17632/7dybx7wyfn.3
2. European ST-T Database DOI: 10.1093/oxfordjournals.eurheartj.a060332

References

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