Sonification of Sleep Data

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## Introduction

Sleep apnea is a sleep disorder characterized by a full stoppage in a patient's breathing while they are asleep. Similarly, hypopnea is a sleep disorder that causes shallow breathing and a reduction of oxygen levels while asleep. Both disorders are related and share similar symptoms, such as snoring, fatigue even after a full night's rest, morning headaches, insomnia, nasal congestion, and weight gain, among others. Sleep apnea and hypopnea can also put individuals at risk for other conditions, such as diabetes, high blood pressure and other heart issues, liver problems, and issues during surgery (due to breathing issues while under anesthesia).

Both sleep apnea and hypopnea have three common types: obstructive apnea/hypopnea, central apnea/hypopnea, and complex (mixed) apnea/hypopnea. Obstructive apnea and hypopnea are caused when a partial or complete blockage of an individual's airway occurs, caused by the narrowing of the throat due to muscle relaxation during sleep. Central apnea and hypopnea are caused by breathing malfunctions while sleeping, normally due to an issue with the nervous system. Complex (mixed) apnea and hypopnea is a result of a mixture of restricted airflow and brain induced breathing issues [1].

Because of the uncomfortable symptoms of sleep apnea and hypopnea present, as well as the health complications they can result in, it is important for both people and their healthcare providers to know if they have one of these disorders. Treatments are available, such as CPAP therapy (which uses a device to supply a steady airstream to a patient). Lifestyle changes such as losing weight, quitting smoking, and limiting alcohol consumption have also been found to alleviate symptoms, which is crucial in minimizing risk of cardiovascular problems (as well as the prior discussed complications) [2].

However, correctly diagnosing a person with sleep apnea or hypopnea can be difficult. Oftentimes, a person will only go in for a diagnosis after their partner reports lack of sleep due to snoring. For people who sleep alone or whose symptoms do not impact their waking life, they may never be diagnosed. The most common method of diagnosing apnea and hypopnea is performing a polysomnography, which involves hooking up a patient to equipment that monitors their oxygen levels, heart function, brain, and lungs for either all or part of the night. Depending on the results, referral to an ear nose and throat doctor or a neurologist may be necessary to diagnose the correct form of apnea/hypopnea. However, sleep studies can take a long time (upwards of many weeks) for results to get back to patients, and the analysis of the data is frequently left solely up to the technician performing the sleep study. Other times, studies can come up completely inconclusive.

Our conversations with Dr. Kara Dupuy-McCauley, our contact at Mayo Clinic, further echoed the sentiment that sleep study analysis often creates more of a nuisance than it should for the doctors analyzing the study. She told us stories of incorrect diagnoses due to a misreading of data by sleep technicians and having to go back over studies by hand to correctly diagnose sleep disorders. This poses a problem for both patients and doctors: patients are not aware of their diagnosis and are not receiving treatment as rapidly as they can, and doctors are having to take time from their other responsibilities to reanalyze data.

Doesn't this make you want to dance? No? Well, it can! The goal of this project was to create a novel tool to aid in the diagnosis of sleep apnea and hypopnea in an exciting, useful, non-invasive, and aesthetically pleasing way. The chosen medium of the project is electronic music tracks that change in response to apnea and hypopnea detection in sleep study data. The purpose of these tracks are to assist in the analysis of sleep data to make the diagnosis of these disorders easier, and in a way that accurately and clearly represents the disorder sonically. One motivating definition is that, in sleep studies, doctors refer to the decreases in nasal pressure, oxygen, and other metrics as "drops". "Drops" analogously exist in electronic music, and in linking the occurrence of "drops" in sleep study data to musical "drops", it is our hope to create an intuitive sensory link that a sleep study technician can accurately diagnose a(n) apnea/hypopnea event by *listening* to the data.

An important feature of the music is that it responds to detection of hypopnea/apnea in real time. That is, the technician listening to the data is able to hear the data as it is occurring (or if the study is being listened to retroactively, they can at least hear the data on an accurate time scale). We also put the aesthetic qualities of the music at the forefront, to ensure that the sonified data was an interesting and engaging experience to listen to. An additional criteria for the music was that it needed to be extremely obvious when a(n) apnea/hypopnea was occurring, so that the diagnosis is clear from the audio. This was a critical design feature, as if the detection algorithm flagged an event as an apnea or hypopnea but it was not made clear through the music, the usefulness of sonifying the data would be lost.

## Methods

### Data Pipeline + Design

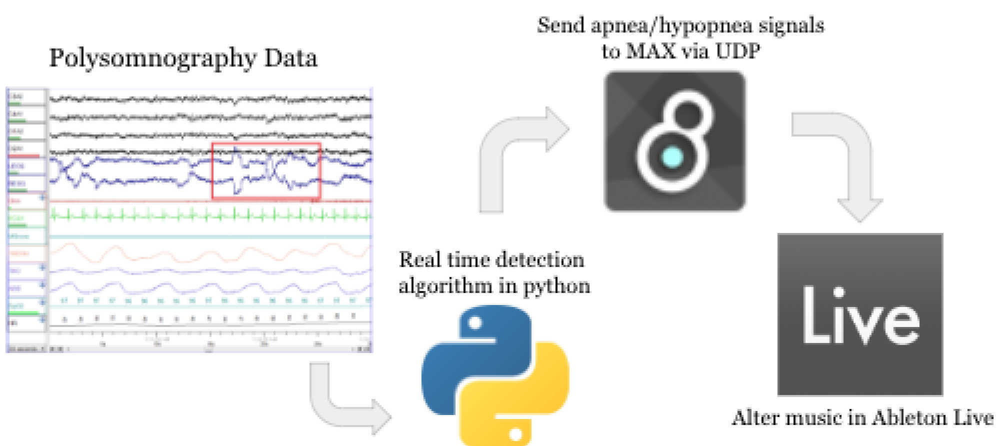


Figure 1: Data Pipeline

The above figure displays the design of our data pipeline to use the polysomnography data to manipulate our electronic tracks. First, the sleep data is read into a python script that runs the real time detection algorithm on the data to identify instances of hypopnea and apnea events. Upon detection of a hypopnea/apnea, a signal is sent from the python script to MAX using UDP. This signal is then processed by MAX and manifests in the music in one of two ways. If a hypopnea is detected, a low pass filter is applied to the music, removing the high frequencies of the music and leaving only the bass and beat. Upon detection of an apnea event, a beat repeater effect is applied, simulating a "beat drop" in the music. The clinical definitions of hypopnea and apnea (discussed further on) used for this project have the potential to overlap, so the combination of audio effects can occur and amplify the "drop".

Data Processing (Algorithm Implementation)

The input file structure contains three columns, nasal pressure, oxygen saturation, and pulse. At this stage in the project, we are only considering the nasal pressure and oxygen signals for hypopnea/apnea detection. Nasal pressure values are sampled at 500Hz, which we resample to 10Hz, and oxygen saturation is sampled at 1Hz. A Butterworth bandpass filter is then applied to the nasal pressure data to remove high and low frequency noise. At this point no additional processing is required on the oxygen saturation data, and the rest of the processing is computed solely on the nasal pressure to calculate the respiration baseline.

The remaining steps to calculate the respiratory baseline is based on the algorithm proposed in the paper "A Real-Time Algorithm for Sleep Apnea and Hypopnea Detection" [3]. Next, we calculate the moving average curve (mac) of the nasal pressure data, by getting the mean value of the nasal pressure signal in every 4 second window (as 4 seconds is the length of the average human respiration. Now, the indices of the rising and falling flags are calculated from the nasal pressure data and the moving average curve. A falling flag is registered if at the prior index (in this case an index is a 0.1 second period due to nasal pressure being resampled to 10Hz) the nasal pressure value was lower than the mac value, and the current nasal pressure value is greater than or equal to the mac value at that index. Likewise, a rising flag is registered if at the prior index the nasal pressure was greater than the mac nasal pressure, but the nasal pressure is less than or equal to the mac nasal pressure at the current index. The equations for the flags are given in figure 2, where s is the array holding nasal pressure values and M is the calculated nasal pressure moving average curve.

$$F_{\text{rise}} = \{s(t-1) < M(t-1)\} \bigcap \{s(t) \geq M(t)\} \qquad (2)$$

$$F_{\text{fall}} = \{s(t-1) > M(t-1)\} \bigcap \{s(t) \leq M(t)\} \qquad (3)$$

Figure 2: Rising and Falling Flag Equations

Using the rising and falling flags, peaks and troughs are identified from the nasal pressure data. To accomplish this, the nasal pressure data is scanned, identifying the minimum value between a falling flag and rising flag as a trough, and the maximum value between each falling flag and the subsequent rising flag as a peak. Both the respective minimum and maximum value as well as the trough index and peak index are recorded.

$$\text{peak} = \max\left\{s\left(F_{\text{rise}} : F_{\text{fall}}\right)\right\} \qquad (4)$$

$$\text{trough} = \min\left\{s\left(F_{\text{fall}} : F_{\text{rise}}\right)\right\} \qquad (5)$$

Figure 3: Peak and Trough Formulas

Next, the initial respiratory baseline is calculated. The baseline is calculated as the mean amplitude of the first 40 respirations, which is determined by the difference between the peak nasal pressure and trough nasal pressure for a single respiration. 40 respirations are chosen because the maximum length of an apnea/hypopnea event is about 120 seconds, and the average person takes 12-18 breaths per minute. The rest of the baseline is generated by using a 20 second sliding window, marking valid respirations as only respirations with amplitudes between 0.5 and 2 times the previous baseline nasal pressure value. If any valid respirations are found within the window, the new baseline is calculated using a weighted average of the previous baseline and the average respiration amplitude from the new window. For the purposes of this project and in line with the findings of the paper our algorithm is based on, the weight factor for the baseline equation is set at 0.8. In Figure 4, A(t) represents the average respiratory amplitude at time t.

$$A_{\text{base}}(t) = (1-\alpha)A_{\text{base}}(t-1) + \alpha\bar{A}(t)$$

Figure 4: Current Respiratory Baseline Equation

Figure 5 shows a graph of the nasal pressure baseline alongside the raw nasal pressure data, with peaks and troughs identified. Figure 6 shows a graph of oxygen saturation from the same dataset. We use both of these signals in tandem to identify hypopnea and apnea events.

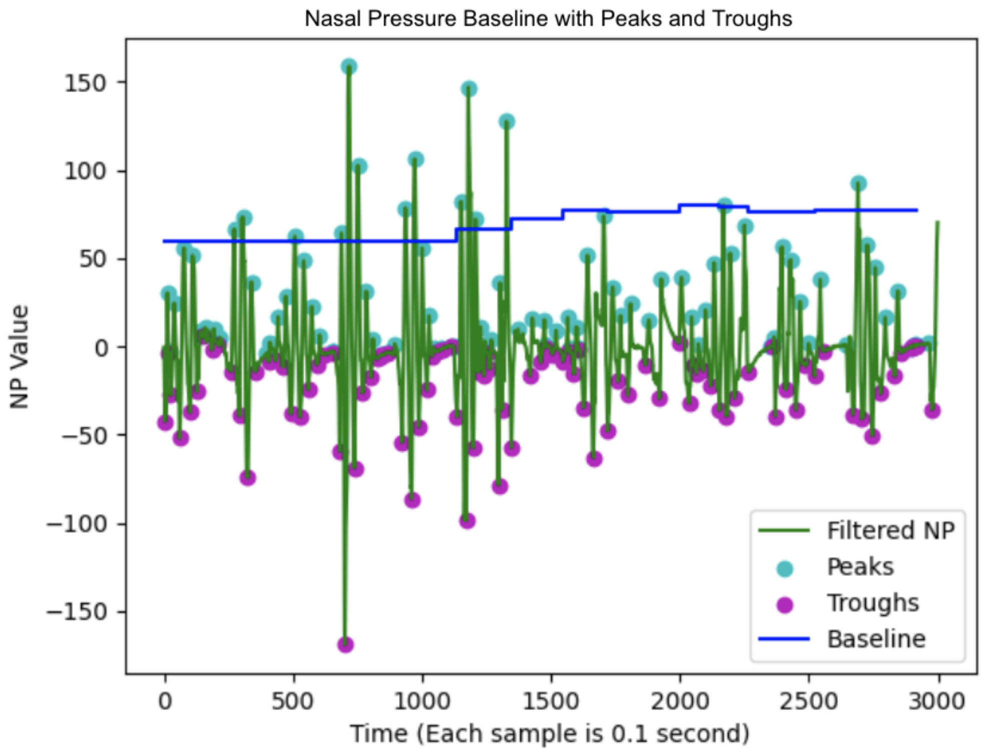


Figure 5: Nasal Pressure Baseline

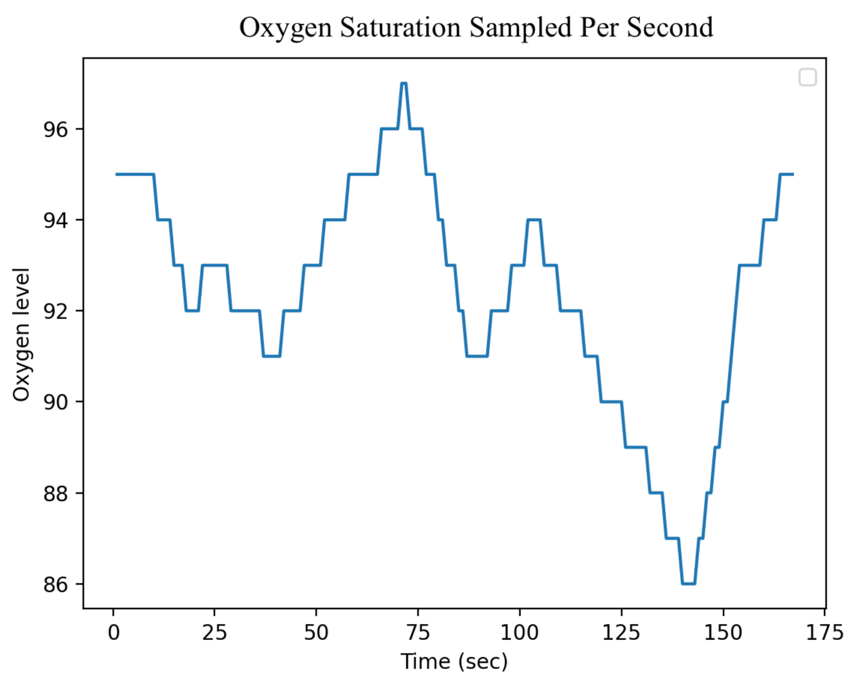


Figure 6: Oxygen Rate

Apnea and Hypopnea Event Detection

There are varying definitions that sleep technicians use when scoring sleep studies to mark hypopnea and apnea events. For this project, we define an apnea event as a 95% or greater decrease in nasal pressure from the baseline [4], and we define hypopnea as a 4% or greater decrease in oxygen saturation at any point [5]. In the final step of the data processing, the nasal pressure and oxygen data is scanned in real time (one oxygen value per second, ten nasal pressure readings per second) and upon detection of an apnea or hypopnea event, a signal is sent to MAX over UDP to trigger a musical effect.

In Ableton Live, as previously discussed, a hypopnea event is represented as a low pass filter on the music, which cuts out all the high frequencies in the song, while an apnea event is represented as a beat repeater effect, which chops the beat into double time. There is not a specific metric to measure how well the sonic effects represent hypopnea and apnea, but empirical demonstrations of the tracks have resulted in positive feedback. We are more than satisfied with how the tracks represent apnea and hypopnea, and believe that a sleep technician could absolutely utilize the tracks to diagnose a patient.

## Results

**Link: Example Track With Nasal Pressure and Oxygen Signal**

https://drive.google.com/file/d/17qmDQhnjZPUBCb1UA1gSlEykxv576FUc/view?usp=sharing

**Link: Example Track - ONLY Oxygen Signal**

https://drive.google.com/file/d/1jsuVwjsBOkQOih75mDZ47LNW0qfPTTY_/view?usp=sharing

Other Accomplishments

A side project for the team this semester was to update the project website, which we worked on throughout the semester. Website Link: https://sleepsounds.cargo.site/

Additionally, we had ongoing contact with Dr. Kara Dupuy-McCauley, our contact at Mayo clinic, to discuss sleep conditions and how to best improve the project, throughout the semester. She was an invaluable resource to us and gave great insight on what direction to take the project this semester and beyond. She was also able to supply us new datasets and research studies to improve our knowledge base.

Future Work

Firstly, one large and exciting project we have coming up is to present to Dr. Dupuy-McCauley's division at Mayo Clinic this fall. We were hoping to be able to present this semester, but due to availability issues with presentation slots, we are looking for a presentation date hopefully sometime in September. We are excited to have the opportunity to present and receive feedback from professionals in the field and to get suggestions on how to further improve the project so it can be of use to them.

As the computer scientist of the team, my work on the algorithmic implementation and data processing will continue. One area of interest is refining the detection algorithm to differentiate between central and obstructive hypopneas/apneas. To accomplish this, we will need multiple datasets from patients that were confirmed to have a specific type of hypopnea/apnea and I will need to research how each type manifests itself in the sleep study data.

Another avenue to explore in the data analysis is using additional signals in the detection of apnea and hypopnea events. Sleep studies contain many data streams, including snoring signals, torso movement, and pulse (which we currently have access to in our test data), but right now we are only basing our detection algorithm on two: nasal pressure and oxygen saturation. If we can incorporate more data into our detection methods, we can likely improve the accuracy of our hypopnea and apnea detection.

I also anticipate looking into the use of machine learning classification methods to make our detection algorithm more accurate. Especially when we incorporate more inputs, it will likely be beneficial to test out different types of models and evaluate which predictors correspond to the most accurate models. With modern machine learning techniques, it is likely that we can achieve very accurate identification of apnea and hypopnea events, and this is an avenue I am very interested in exploring as this project moves forward.

References

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