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Data Sonification Using Pretty_MIDI and Jupyter Notebook

Abstract

Data sonification has received some attention in the past, particularly in the 70s as an attempt to create art and more recently as a potential tool in medicine. The most famous of these have used EEG data to create sound, such as Alvin Lucier's audification projects and recent research undertaken by CCRMA at Stanford. While exploring these projects, I came to the conclusion that periodic data, such as circadian and ultradian rhythms that occur in human biology, would be extremely suitable to sound mapping. In this paper I give a brief overview of attempts to sonify data and audify circadian rhythms before presenting my project, which takes various temperature data sets from a csv file and maps them to sound in a way that accurately reflects patterns in the data (and between the different sets). The result is one solid step towards a long-ranging goal of coordinating multiple types of circadian and ultradian data to sound in order to reflect a comprehensive overview of the changes within a human body in relation to time. The overarching idea is that sound is an underutilized but illuminating way to perceive data, one that is potentially more naturally suited to some types of data than the typical visual methods we currently use to representation them.

Introduction

Music is number in time; in theory, anything that can be measured in relation to time can be used as input to compose sound in a way that bears a meaningful relationship to the original thing that was measured. In the past, mathematicians have delighted themselves by comparing

the patterns found in other fields of mathematics to those found in music. For example, astronomers have noticed that the rotation period of Venus is exactly two-thirds of an Earth year, a musical fifth (and if their orbits were traced on a piece of paper, after eight Earth years one would see a completed geometric pattern of a perfectly symmetrical flower). Many things in life — from planets to seasons, sleep schedules, and electrons — orbit, oscillate, or rotate, and so these seemingly coincidental harmonizations between otherwise unrelated phenomena are happening around us all the time, every day and largely invisible. Surprisingly, the oscillations of human body, known as circadian rhythms, are just beginning to be studied and scientifically understood by the Western world; in fact, the term “circadian” was only recently coined in the 1950s by Franz Halberg. As an emerging and personal discipline, the idea of sonifying chronobiological data to hear the inherent ratios struck me at once as potentially useful and intensely beautiful.

Historical Precedence

There is plenty of significant precedence in data sonification, and even with human data, although in my research I found little on circadian rhythm sonification. David Rosenboom put together a book of early experiments in biofeedback (3), and in it chronicled perhaps the most famous example of using human rhythms for musical purposes: Alvin Lucier’s *Music for Solo Performer* (p. 60). In that piece, Lucier used an EEG cap to audify brainwaves, even going so far as to lever his own mind’s electricity as a means of playing other instruments. More recently, researchers at CCRMA Stanford designed a device that sonifies epilepsy data, and makes it easier to perceive patterns that are useful for understanding a patient’s health (2). In general, the

art and science of using circadian rhythms for musical purposes is still in its infancy, but I believe it holds an amazing amount of potential. This conclusion is often echoed at the end of many respected articles on topics in the field, such as this one from a textbook collection of studies in music within other scientific disciplines: “... Sonification may provide a deeper understanding of complex body rhythms. A specific stimulation of these rhythmic structures in real-time sonification, or by means of much more complex structured sonifications with a richness as is encountered in music, is a promising new approach for further investigation. (1, p. 22).”

Data Sonification Project: Current Status and Methods

Building on the history and on the massive availability of technological resources available today, I decided I wanted to begin sonifying specifically human circadian rhythms with the ultimate goal of being able to sonify multiple rhythms from a singular source in a way that is accurate, comprehensible, meaningful in demonstrating the relationships between different rhythms, and easy (even beautiful) to listen to. In other words, I wanted to build a kind of “human symphony” that is informative as well as beautiful. There are many approaches to doing this, as well as many potential pitfalls for inaccuracy. There has to be a choice in what part of sound to map data values to (ex. pitch, volume, timbre), whether different rhythms should be represented by different instruments or different frequencies, etc. And then one has to deal with the fact that the data values that are being mapped may not necessarily relate at all, in which case setting them to sound may lead to a listener hearing correlations that do not actually exist. In addition, using a tuning system like our 12-tone scale makes the data easier to map to MIDI, but

less accurate overall because then it is being “bucketed” at divisions that do not exist in the actual information. Finally, one has to make sure they are being true to time; EEG has a very high periodicity as compared to temperature data, and hearing a proportional relation between the two requires a little bit of tricky math.

At this point, I feel the project has taken its second step: still a ways away from the final destination, but definitely a well-formed structure built on a solid foundation. In the first step, I started out small, choosing three temperature datasets (core, distal, and axial) taken from one subject, Azure Grant, a student researching circadian rhythms at UC Berkeley, over a three day period. The tools I used were Jupyter-Notebook, IPython and the Python library PrettyMIDI, and the DAW Ableton Live — all software (though the hardware used to collect the data is a rather innovative sensor in the process of commercial development). Even though all three use the same units in relation to time (Celsius), I decided it would make sense to generally map higher values representing higher energy to higher frequencies (i.e. pitch), since high sounds are the result of higher energy. I also chose to represent different datasets with different instruments, or timbres. This way it is easy to pick any single dataset as well as to hear how it “blends” with the others. The data I had all came from one person over the course of 72 hours, but the resolution is one sample per minute — much too slow for the ear to pick up any patterns. So I compressed the data by treating each minute like a tenth of a second — the whole piece shrinks from 72 hours to around 4 minutes in length. I also lowered the velocity from a default of 100 to 50, and let each note ring for a tenth of a second. Originally, I converted the data from a measurement of Celsius to a MIDI note number (using the formula $\# = 69 + 12 \log_2(\text{freq.} / 440 \text{ Hz})$) and tweaked the values to fit a range where all the data could be perceived, but later would adjust this process so

that the piece was not in Equal Temperament tuning, the notes were spread over the same octave ranges, and the math was based on normalized values. But for this first pass, the result seemed to me to be the clear representation of the data while being the easiest to listen to for four minutes straight.

After producing a piece that really was the sonified data from three correlated sets, I wanted to go back and really refine what I had; in other words, rather than continue adding new datasets (which I am currently waiting on from Azure and her team at Berkeley), I wanted to dive deep into the data I already had and retrieve more information from it, as well as make their sonified representations much more accurate and meaningful. Larry Polansky, a professor of music at UC Santa Cruz, gave me some guidance in adjusting the ranges and pitches so that they more realistically correlated to the data. First, we decided to normalize all the temperature values across the three datasets using the global minimum and maximum values; then we learned how to use PrettyMIDI's pitch bending functionality to develop control for taking numbers and mapping them to a pitch bend range. I chose the octave spread for all three sets to be from A4 (440 Hz) to A6 (1760 Hz). To achieve this mapping from the normalized Celsius value I devised a formula:

$$Frequency = (OctaveRatio)^{(NormalizedCelsius)} * FloorFrequency$$

* Octave Ratio is the ratio of octaves to whatever the Floor Frequency is (ex. 4:1 is two octaves, so if the Floor Frequency is 440 Hz, the frequency two octaves up is 1760 Hz)

From there I was able take the original formula for converting frequency to MIDI, use the remainder of the frequency float value to retrieve an accurate pitch bend value (I only use whole numbers for the MIDI conversion), and set the MIDI note number and pitch bend value to a time

value, which again was a tenth of a second for one minute of data. Now I had all our data objectively represented in a non-tuned system, with all the datasets spread across the same ranges. Listening to it, I was for the first time really surprised and fascinated by what I heard; the pitch bending is eerie and gives the piece a feeling of life as opposed to its static and repetitive predecessor. The researchers agreed, though they were more impressed by the level of accuracy the sonification had now attained.

There were a few more things I still could still do with the data I had before adding more sets (and I am sure there still are, now). The next thing I did was to start taking different statistics on the data; covariance and correlation confirmed the obvious, which was that the distal and axial sets were positively correlated, and both inversely correlated with the core dataset. This has not been really helpful yet, although it might be in the future. What was more interesting was creating new arrays from the existing sets using first-order differential calculus; doing this for all datasets, I now had three completely new arrays to sonify. Leaving out values of zero (indicating no change from one sample to the next), what could be heard was a meaningful accompaniment to the data that could communicate movement of the data. In fact, with the original dataset MIDI turned off, the difference equation MIDI could accurately convey a sense of the data, although now the piece was pointillistic rather than three streams of sound, which I actually think is a more efficient and clear way of perceiving the data. Using the next orders of calculus, this concept could be taken further to reveal things like local minima and maxima in the data, although I have not taken that step yet. What I did do was add the overall maxima and minima for each individual data set to a percussion track. What we now had at the end of the second part of this project were the three normalized and pitch bended data sets, their corresponding and

almost percussive difference equation sets, and an event-related percussion track that indicated important moments in the original datasets. While I am still experimenting with timbres and even multiple octaves, I am constantly learning more about the data as it is being revealed to my ears, like unexpectedly frequent events, or the confirmation of periodic “cluster points” in the data.

Future Considerations

While I feel the project in its current form is now interesting and useful from both a musical standpoint and a scientific one, I want to add more breadth and more depth to it: breadth in terms of new datasets, and depth in terms of deeper, more revealing statistics. These first few steps have built-up and refined the accuracy of the sonifications and made them bearable to listen to; I now want to further improve the piece from an aesthetic standpoint and expand the project. Azure, her peers, and I are continuing this project and working together to optimize it for their research; in this case, that to me means the best musical outcome as well, as the whole purpose of this experiment is to create music that says something important about the numbers that created it. As I mentioned before, I am expecting to have EEG, EGG, EKG, and activity datasets within the next few weeks. And very far down the road, I would like to look into the possibility of doing all of this data mapping in real time, with a human wearing sensors, without having to go through MIDI first. This step, should it come to fruition, would make the piece truly generative (the composer would really only be adjusting equations and choosing parameters), and could also be a more responsive tool for investigating the human body.

Works Cited

1. Colin Raffel and Daniel P. W. Ellis. [*Intuitive Analysis, Creation and Manipulation of MIDI Data with pretty_midi*](#). In Proceedings of the 15th International Conference on Music Information Retrieval Late Breaking and Demo Papers, 2014.
2. Haas, Roland, and Vera Brandes. *Music that works Contributions of biology, neurophysiology, psychology, sociology, medicine and musicology*. Vienna: Springer Vienna, 2009. Print.
3. "New Device Listens to Brain, May Help Epileptic Patients ..." N.p., n.d. Web. 14 Feb. 2017.
4. Rosenboom, David. *Biofeedback and the arts: results of arly experiments*. Vancouver, B.C: A.R.C. Publications, 1976. Print.