SONIFICATION STRATEGIES FOR DEEP-SPACE MATERIALS

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What are you trying to sonify? Why?

Since before the written word and long before any semblance of modern science, humans looked to the stars. Instinctively I chose to sonify data from a variety of astronomical sources drawing, perhaps, from the same sense of curiosity that all humans have but, more practically, I gravitated toward astronomy data because it frequently lends itself to translation to the audio domain—waves, times series, spectroscopy, etc—and because so much of what exists to be known in the universe does so outside the range of many human senses (such as sight) but also orders of magnitude beyond human intuitions of space and time relations. Sound, already being of an abstract nature, feels like an ideal medium to transmute information that, as it pertains to human perception, also exists in an abstract form.

Discuss your process of data organization and formatting.

With each dataset, my goal was to capture the "essence" or the "spirit" of what the data represented and then scale it in a way that would be conducive for mapping to auditory parameters. For instance, is the data wavelike? That is, does it oscillate between relatively equidistant positive and negative bounds? In that case, that particular data was typically scaled to the range of [-1,1] to be used as a waveform or LFO. Is it mostly static with sporadic impulses in one direction? Data like that might be used to trigger sound events or control filter envelopes.

Overall, the strategy was simply to "tidy-up" and format the data in a way that was oriented toward sound synthesis (so, lots of scaling between [-1,1] or [0,1]) but, at the same time, general enough as not to necessarily be tailored to any specific auditory parameter alone. The goal was to equip myself with a palette of material that could be experimented with in the sound domain in a free and flexible manner, but also maintain the characteristic qualities that the raw data possessed.

Justify your parameter mappings. For each data parameter, explain why it is best suited for the selected sonic feature (be as specific as possible).

Set 1: Exoplanet Detection

Exoplanets are simply planets outside our solar system. They are typically far too distant to be seen with conventional telescopes, however their presence can be detected by observing the changes in magnitude of the star they orbit where sharp, transient drops in magnitude indicate that an object (or objects) have passed between the star and the observer. Despite the profoundly advanced technology employed, the method of detection is actually relatively simple and relies on a phenomenon easily reproduced on a much smaller scale. For example, when passing your fingers between your eyes and a singular lightsource such as a streetlamp or the sun, the lightsource is reduced in brightness but not obscured completely. I wanted to sonify this phenomenon in a way that would be equally straightforward and recognizable.

The data itself is presented as a time series where each of the over 3,000 frames represent one snapshot of a host star's magnitude at one moment in time. When plotted in sequence, a clear waveform emerges. Each row (representing the time series magnitude of an individual star) was scaled on the range [-1,1] and exported as a text file to be read by the **coll** object in Max. In a Max patch, I created a single instance of a **resonator~**[1] object modeling a resonant bell sound which filters a constant stream of pink noise. Here, the resonant bell timbre represents the luminosity of a target star. The exported magnitude data is used to modulate a simple lowpass filter so that values below 0 reduce the filter's center frequency and values above 0 increase the center frequency. As a playhead runs through the time series, the result is like an auditory analogy to the phenomenon used to detect exoplanets.

Set 2: Pulsar Profiles

Pulsars are a type of Neutron star that emit radio waves across vast distances. Because of the relatively periodic nature of these emissions, they were first speculated to be artificial signals. Recently, machine learning algorithms have been employed to detect potential pulsars and have rendered the old-fashioned radio-astronomy technique of manual detection essentially obsolete.

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[1] From the CNMAT Externals library.

For this reason, I wanted to create an easily-accessible environment where a user could browse a library of pulsar candidates for recreational or didactic purposes.

Presented is a catalogue of over 12,000 pulsar candidates. However, this time, the data is not presented as a time series—all time series information has been averaged to single numerical values across eight interrelated parameters. Most of the categorical values have been either scaled to the range of [0,1] or left “raw” and scaled in a variety of ways inside the Max patch.

The concept was to create a patch that resembled a radio-like interface that communicated information in a direct, almost universally understandable way much like a Gieger counter or sonar but, at the same time, have an ambiently pleasing quality reminiscent of windchimes. Because frequency/pulse is integral to the profile of a pulsar, the Mean of the Integrated Profile (essentially, the average of the pulsar’s periodicity) is represented in two ways: first as a repeating “click” proportional to the Mean of the Integrated Profile and second as a more sonorous bell-like timbre that also repeats proportionally but several octaves lower.

The reason for representing one parameter in two ways serves to not only emphasize the importance of this parameter but also to provide additional material to be modulated by the remaining, overlapping parameters. Specifically, the Standard Deviation of the Mean of the Integrated Profile is represented by the rate of stereo panning on the bell-tone and the Skew and Kurtosis are respectively represented by the placement of the central frequency and Q-value for a resonant filter applied to the “click”.

Additionally, as the frequency of the pulsar increases, the resonant model used on the bell-tone is interpolated between two discrete models: one modeled after a pizzicato contrabass (for lower frequencies) and one modeled after a chime-like bell (for higher frequencies). This change in timbral quality provides additional feedback about the pulsar candidate.

Set 3: Star Cluster Spatialization

Stars are typically found in dense clusters (such as galaxies or globular clusters) that contain so many individual stars, they are often collectively regarded as one single entity.

The data is presented as a collection of x, y, z coordinates for 64,000 stars across 19 keyframes. Each frame also contains velocity data for each star at that point in time and space.

Though this dataset is a simulation of such a cluster, the sonification methodology could be applied to observed data.

The inherent spatial quality of the dataset was something I wanted to translate directly into the sound domain but, because it is presented in three dimensions, simple stereo panning would not suffice. To achieve the sense of “3D sound” I used the **ambiX** ambisonics library for Max. Of the 64,000 total stars, only 24 randomly sampled stars are simulated at any given time but it would be conceivable to simulate all 64,000 at once using the functionality of something like **jitter**.

Pitch density is determined by the average velocity of each star at each keyframe where high velocity corresponds to increased deviation from the central pitch and lower velocity results in movement toward the central pitch. The overall effect is that of a singular tone cluster gradually shifting in density and spatial distribution over a period of time.

How do you expect a listener to perceive the overall sound?

Ideally the listener will perceive each sonification setting as reminiscent of the source data. That is to say, they should feel as though they are hearing a sonic representation of the corresponding phenomenon.

How is the sonification advantageous over other means of data presentation?

The advantage of each approach depends on the goal of the user. In the case of exoplanets and pulsars, machine learning algorithms reliably outperform humans in detection and classification so sonification does not offer an advantage over other methods. However, if the goal is didactic or recreational, sonification offers a different mode of perception that can better convey what the data represents.

Sonification also presents a unique advantage in the domain of accessibility. Phenomena like the fluctuation of a star’s magnitude or the shifting spatial positions of a star cluster are difficult to convey to someone with impaired vision but these respective examples translate almost 1:1 to the sound domain where a listener with a visual disability can easily use other sensory faculties to comprehend the data with little loss of information.