’Acid_Hack’

An Electroacoustic Piece for MEG Data and Live Interaction

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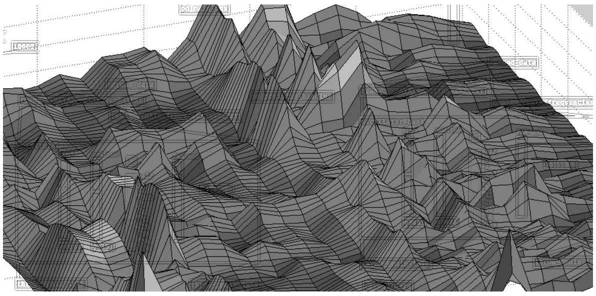

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Concept

The composition presented in this paper was realized through the collaboration between neuroscientists and a composer of electronic music. Starting point for the sonification project was a set of Magnetoencephalography (MEG) recordings, which featured samples from a person in normal condition and under the influence of LSD. In an attempt to represent the differences in the state of brain and perception with and without the influence of LSD the composition comprises two parts, connected with an interlude.

Both parts are composed of a synthesis layer, which is driven by the pre-processed MEG data and a layer of processed recording (Smith, 1991), which aims at representing the perceptual domain. Each layer was used to illustrate the change in the perception of a being under the influence of psychedelics, respectively LSD.

In order to achieve an audible difference between the states through sonification of the MEG data, the neuroscientists settled for finding features within the data, which best discriminate between the two states. These are then used to drive an additive synthesis engine, which will be described in the following section. The layer of processed recordings contains rather plain soundscapes during the ’normal part’, whereas it uses copious manipulation methods in the ’LSD-part’ to create an abstract scenario.

Marking the transition between the two states, the interlude is created from a talk given by Robin Carhart-Harris during the session, heavily processed with granular synthesis.

Realization

The core of the sound synthesis, the additive model, is built from eight oscillator banks, each featuring 30 oscillators. This amount is sufficient for creating rich harmonic structures. Each bank is configured to contain harmonically coupled partial tones (Levine and Smith, 1998; McAulay and Quatieri, 1986), which are modulated by the MEG data:

$$y(t) = \sum_{n=1}^{N_{part}} \left(a(n,t) + a_{mod}(n,t)\right) \sin(2\pi(n f_0(t) + f_{mod}(n,t))\ \ t) \tag{1}$$

The global weighting function $a(n,t)$ is a basic spectral envelope for the harmonics. Different envelopes have been tested and applied, starting from a simple decrease with $a(n) = \frac{1}{n}$ to a parametric modeling of the spectral shape with a piecewise linear model containing three formants (see Computation of Spectral Envelope below). The functions $a_{mod}(n,t)$ represent the time-varying deviations of the amplitudes from the spectral envelopes. They are extracted from the MEG data. Their extent can be specified in the stage of data preparation.
The functions $f_{mod}(n,t)$ represent the deviations of the partial frequencies from the strictly harmonic model. Analogous to the amplitude terms, they are derived from the MEG data in the preparation stage.

For the stereo version, each partial is additionally panned between the two speakers, using a random sequence, in order to enrich the spatial image. The panning strength of all partials can be controlled in real-time with a single control value.

The processed recordings were created with granular synthesis (Roads, 2006) and phase vocoder techniques for time stretching and pitch shifting. Unlike the additive synthesis, this part is not data-driven, but controlled by the performer. Some components were pre-recorded and arranged in the audio sequencer.

All sound synthesis procedures were realized in Pure Data (Puckette et al., 1997). Several 'qlist' objects managed the sequencing of the partials' amplitudes and frequencies. Ardour was used as underlying audio sequencer and synchronized with Pure Data using Open Sound Control (OSC).
Two MIDI interfaces allowed the live-interaction with the synthesis environment. Several parameters of the oscillator banks were controllable in real-time, accessible through a motorized fader bank.

Computation of Spectral Envelope

As mentionned earlier, the function $a(n,t)$ where weighted using a spectral envelope that were allowed to evolved in time. Namely, we defined 3 'sweet points' (corresponding to formants of the global spectral envelope) on the spectral envelope at 1/4, 1/2 and 3/4 of the maximal frequency. The envelope is then a function of time and frequency. We will referer to the spectral envelope in continuous space for frequency and time as $env(f,t)$ (then $a(n,t)$ is the value at discretized frequencies such that $f = n \times f_0$) . We hold the values of the three sweet points constant as well as the values at the boundaries $f = 0$ and $f = F_{max}$. Finally the remaining values for a sclice of the matrix across frequency and at a given time T ($env(f, t = T)$, i.e. t is fixed) are found by linear interpolation. The position of the 'sweet points' on the frequency axis is then modulated by a feature from the MEG. This feature is also zscored and scaled such that the maximum variance we get from it will translate in a modulation of $\delta f = 2\text{Hz}$. Here we used the entropy $entr_n(t)$ (see below 'Entropy time series') at different electrodes to modulate the spectral envelope. That is for each time t, $env(f,t)$ is computed by interpolating between the following points

$$\begin{aligned}
a(0,t) &= 0.5 \\
a(1/4 * entr_n(t), t) &= 1 \\
a(1/2 * entr_n(t), t) &= 0.5 \\
a(3/4 * entr_n(t), t) &= 1 \\
a(1,t) &= 0.1
\end{aligned}$$

Where we used a normalized F_{max}. This processing results in a smooth surface, defined across time and frequencies, that we can apply to weight the amplitude of each oscillators according to their respective frequency. The sound is then shaped by an overall 'formant-like' structure that evolves in time according to features in the MEG data.

MEG Data Processing

Time frequency representation

We focused on whole-head MEG recordings from a single participant (Carhart-Harris et al., 2016) that were made available in this project. The signal was originally sampled at 1200 Hz (0{300 Hz band-pass) and after extensive cleaning was down sampled to 600 Hz and separated into 193 epochs of 2 seconds each. We applied the continuous wavelet transform (CWT) using Morlet wavelets to inspect the time-frequency signature of each epoch independently. Following (Cheyne, 2013) we divided individual spectra into the commonly inspected frequency bands: 1-4 Hz (delta band), 4-8 Hz (theta band), 8-13 Hz (alpha band), 20-30 Hz (beta band), 30-40 Hz, 40-50 Hz, 50-60 Hz, 60-70 Hz, 70-80 Hz (gamma bands). Magnitude for each band was then estimated using the absolute sum of each band. This procedure was performed independently to the two data-sets (LSD and placebo) across the two runs and 271 channels and produced our feature space which contained 2981 features per epoch.

Feature selection

As our brain to music realisation approach require only a few relevant neuronal time series, it was necessary to reduce the dimensionality of the feature space while preserving only the most discriminative information (i.e. between LSD and placebo). Therefore, we applied feature selection by training partial least square discriminant models combined with Monte Carlo sampling to each band independently treating the first run of each time-point as training data-set and cross validating the models using a 70%-30% hold-out split. Further validation was performed using the additional runs epochs. Classification accuracy converged on a set of 110 features that exhibited near perfect separation between conditions. Remarkably, these features seemed to match previous finding about neural correlates of the effect of LSD on the brain (Carhart-Harris et al., 2016). Namely, alpha band power in magnetometers of the parietal areas were among these 110 features. We then used random sampling across these selected features to create four sets of 30 oscillators and produced input signals for the acoustic realization.

Entropy time series

Another feature taken from the data and used to modulate our bank of oscillators was the entropy. Lebedev et al., (2016) mention the increase of entropy in the LSD condition. To compute the time course of entropy at each sensor, we analyzed the entropy in overlapping time-windows of 2 seconds. In each window, we binned the data using a fix number of bins as determined by the Freedman-Diaconis rule (Freedman and Diaconis, 1981) which allow us to estimate the probability distribution density $p(x)$ within that time window. We then computed the entropy as

$$E = -\sum_x p(x)\log(p(x))$$

The amount of overlap was then fixed at 50% and the data were resampled to match the final duration of sound segments (e.g. 5min per condition, sampled at 50Hz for $a_{mod}(n,t)$ and $f_{mod}(n,t)$ time series) to give a feature time series for entropy $entr_n(t)$ for sensor each n. We found, on this single subject, significant differences in variance and mean of entropy values across time in some electrodes although it is difficult to argue it was sensitive to change of brain signals and not only to experimental factors given the little pre-processing done.

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