Berkleee College of Music

The Sound of Soul: Biofeedback Controlled Music Generation and Sound Design

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Master of Music in Production, Technology, and Innovation

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Abstract

The aim of this project is to develop a system that allows biofeedback to be used as a creative musical tool through music generation and sound design. This system uses brainwave data from an electroencephalogram, as well as electromyography muscle activity. This biofeedback is then interpreted by a machine learning neural network which can be trained to classify the user's psychological or physiological state. This determination will then be used to control a generative Artificial Intelligent MIDI generator or other MIDI Continuous Controller signals. The raw biofeedback, averaged brainwave amplitudes, and Fast Fourier Transform of the EEG signal can also be used to control MIDI generation and Digital Audio Workstation parameters directly, and for synthesizer generation and timbral control.

Keywords: Biofeedback, Artificial Intelligence, Neuroscience, Improvisation, Electroencephalogram

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Glossary

Biofeedback – the measurement of physiological activity such as brainwaves, heart function, breathing, muscle activity, and skin temperature.[1]

Electrocardiogram (ECG or EKG) – a device that measures human heart rate

Electroencephalogram (EEG) – a device that detects and records electrical brainwave readings obtained from measuring voltage a certain points of the scalp.

Electroencephalography – the practice of collecting EEG data, see *Electroencephalogram*

Electroencephalophone – an instrument which uses EEG data as a sound source or modulator

Electromyogram (EMG) – a device which measures the electrical activity of muscles

Fast Fourier Transform (FFT) – an algorithm that converts a signal to a representation of its composite frequencies and vice versa

GUI – Graphical User Interface, a program for displaying and controlling data within software

Long Short Term Memory (LSTM) – a type of deep learning RNN well suited to MIDI generation

Low Frequency Oscillator (LFO) – a slow moving oscillator used for audio effects and synthesizer control

Musical Instrument Digital Interface (MIDI) - a protocol for interfacing musical instruments and software

Open Sound Control (OSC) – a protocol for interface audio visual hardware and/or software

Processing – A Java based programming environment

Recurrent Neural Network (RNN) – a common of machine learning algorithm architecture

Root Mean Square (RMS) – a mathematical function for calculating the average value of continuous signal

[1] Applied Psychophysiology & Biofeedback, "Home - AAPB," Aapb.org, 2019, https://www.aapb.org/i4a/pages/index.cfm?pageid=1.

1. Introduction

Access to music education is a luxury that eludes many children globally. Music programs provided by public schools suffer inconsistency and inequality, and many families lack the means to enroll children in extracurricular music programs or hire private instructors. According to a study from the United Kingdom, "families with a total household income of less than £28k are half as likely to have a child learning an instrument as more affluent peers with a family income of £48k or more."[2] A similar patterns emerges for children based on their parents' level of education, with, "[n]early half (48%) of children who have parents who are educated to university level will learn an instrument, compared with one-fifth (21%) at secondary school level."[3] This article concluded that, "[w]ith certain children priced out of learning musical instruments, we may well only be hearing the songs and sounds of the affluent in years to come. Those from poorer backgrounds will, unfairly, be increasingly under-represented within the industry."[4] Researchers in India found a similar dearth of music education within their educational system, noting that in Indian public schools, "[t]he arts are reduced to tools for enhancing the prestige of the school…[b]efore or after that, the arts are abandoned for the better part of a child's school life."[5]

Students with disabilities also face significant challenges in music education and often find musical expression to be an unachievable goal. "As a field, music education prides itself on

[2] Access to Music Lessons Dying out for Poorer Families, "Access to Music Lessons Dying out for Poorer Families," Musician's Union, June 11, 2018, https://musiciansunion.org.uk/all-news-and-features/access-to-music-lessons-dying-out-for-poorer-families.

[3] Ibid

[4] Ibid

[5] Vishal, "The Face of Music Education in Schools in India the Face of Music Education in Schools in India View Project Investigating the Technology Integrated Music Education in Indian Schools View Project Dr. Vishal," Gandhi Conference 2015, 2015, https://doi.org/.

championing diversity and inclusivity, but disability is often omitted from these discussions, and people with disabilities are treated unequally in music education settings."[6] Music curriculums are very rarely designed in a way that allows for music students with disabilities to have fulfilling musical experiences. "[M]any major texts in the field frame disability primarily as a personal attribute, and focus on helping students with disabilities to participate in traditional school music activities such as concert band and choir,"[7] rather than reimagining ways in which students with disabilities could achieve meaningful musical expression. And while not by design, many traditional musical instruments and idioms are impossible or at least far more difficult for students with disabilities to achieve proficiency.

There is a genuine need therefore to create more inclusive systems of musical creation, tools to allow anyone, regardless of prior access to music education or disability, to experience meaningful expression, artistic fulfilment, and overall enjoyment through the creation of music. Thus this project's aim to create a set of tools that allows raw biofeedback to be applied to a variety of musical applications through melodic generation and sound design. The resulting tools should be able to provide instinctive, biofeedback-based music generation for the inexperienced or disabled, as well as enhanced expressive capabilities for experienced musicians.

A simple implementation of biofeedback in music involves applying the signals directly to an oscillator or existing audio signals to modulate pitch, amplitude, and/or timbre. This is a useful tool for enhancing musical expressivity when modulating amplitude and timbre, but pitches generated directly from biofeedback can be unwieldy, interesting for avant-garde or experimental applications, but unsuitable for many conventional musical situations. To solve

[6] Adam Patrick Bell, "Hacking, Disability, and Music Education," International Journal of Music Education (2020).

[7] Ibid

this, the raw data can be processed through music generation algorithms and generative machine learning networks. These processes will automatically generate melodic content, using the biofeedback data to influence generative parameters such as tempo, pitch range, distance between consecutive pitches, rhythmic variation, and so forth. So while a brain-computer interface (BCI) that renders notes directly from conscious thought remains an elusive problem based on current technology and understanding, this system would provide a tangible method of musical creation using only the user's brainwaves combined with other biofeedback sources.

2. Review of the State of the Art

2.1 Biofeedback Music

2.1.1 Biofeedback

Biofeedback is defined by AAPB (Applied Psychophysiology & Biofeedback) as "a process that enables an individual to learn how to change physiological activity for the purposes of improving health and performance."[8] Electronic sensors are employed to measure a variety of physiological data, such as brainwave, heart rate, muscle activity, skin resistance, blood oxygen level, breathing, and body temperature. "The presentation of this information — often in conjunction with changes in thinking, emotions, and behavior — supports desired physiological changes,"[9] and thus changes in thoughts and emotions can be detected through analysis and correlation of this data. Some of this data, particularly from an EEG, is quite noisy, so signal

[8] Applied Psychophysiology & Biofeedback, "Home - AAPB," Aapb.org, 2019, https://www.aapb.org/i4a/pages/index.cfm?pageid=1.

[9] Applied Psychophysiology & Biofeedback, "Home - AAPB," Aapb.org, 2019, https://www.aapb.org/i4a/pages/index.cfm?pageid=1.

filtering and classification through machine learning are often used to make the data more readable and usable.

2.1.1 The Electroencephalophone

The electroencephalogram (EEG) is a device which records, "electrical potentials produced by brain cells…as detected by electrodes placed on the scalp".[10] The first human EEG readings were recorded by German psychiatrist Hans Berger in 1924, and became useful as a tool for researching epilepsy and other neurological disorders.[11] Starting in the mid-20th century, avant-garde musicians began to experiment with using EEG voltage signals as part of their compositions. In 1965, American experimental composer Alvin Lucier completed "Music For Solo Performer", a composition in which the performer's Alpha waves are used to trigger an ensemble of motorized percussion instruments. In this case though, the resultant music is an artistic sonification of the performer's Alpha waves, not a conscious or controllable musical creation. "[In] Music for Solo Performer, data are not used to make brain activity understandable but rather to emphasize the nature of thoughts and mental processes."[12]

Another notable experiment with EEG signals in music composition came from Finnish synthesizer pioneer Erkki Kurenniemi, who created a purpose built EEG-based synthesizer and designed for it a composition to be played by a group of sleeping musicians. "DIMI-T, dubbed

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[10] Graetzer, Daniel G., PhD. "Electroencephalography (EEG)." Magill's Medical Guide (Online Edition), 2020. http://search.ebscohost.com.catalog.berklee.edu:2048/login.aspx?direct=true&db=ers&AN=87690502&site=eds-live.

[11] Erik St Louis et al., Electroencephalography (EEG): An Introductory Text and Atlas of Normal and Abnormal Findings in Adults, Children, and Infants (American Epilepsy Society, 2016).

[12] Volker Straebel and Wilm Thoben, "Alvin Lucier's Music for Solo Performer: Experimental Music beyond Sonification," Organised Sound 19, no. 1 (February 26, 2014): 17–29, https://doi.org/.

the 'Electroencephalophone', was played with brain waves, picked up by electrodes on the player's earlobes. In spite of the name, DIMI-T was not digital, but analogue in nature. The EEG signal from the user's brain waves was amplified, band-pass filtered and used to frequency-modulate a VCO inside. DIMI-T was intended for group use. A quartet of musicians, each equipped with a DIMI-T, would go to sleep listening to each other's generated sounds, and Kurenniemi envisioned that their brainwaves would synchronise during sleep."[13] This composition ultimately was never performed, but similar to Lucier's composition, the EEG signal would have been used for its artistic value as a human brainwave. There is no attempt to parse meaning or understanding from the performer's EEG readings.

With cheaper and less expensive computers however, music technologists have begun to create electroencephalophones that attempt to divine melodic content from human thought. One of the most successful of these projects has been created by University of Washington researcher Dr. Thomas Deuel, who has created a electroencephalophone that is capable of generating musical notes solely from EEG readings. However, he notes in a 2016 lecture, that there are a few caveats: successfully performing with this instrument requires a tremendous amount of training on the part of the user; the instrument also relies on simple mental techniques and using "the motor and visual cortex to trigger the signals"[14], and quantizing such techniques to predetermined musical scales. The instrument therefore, is not directly reading the notes that a user is thinking about, but rather responding to pre-trained stimuli.

[13] John Alex Hvidlykke, "Pioneer of Digital Synthesis," Sound on Sound, September 2013, https://www.soundonsound.com/people/pioneer-digital-synthesis.

[14] Microsoft Research, "Studio99 Presents: Thomas Deuel and His Encephalophone," YouTube Video, *YouTube*, June 27, 2016, https://www.youtube.com/watch?v=Ad2UmTv33DU.

2.1.2 Other Types of Biofeedback Instruments

Besides EEG data, other types of Biofeedback have had limited musical applications. A 2008 project conducted by Steve Mann, James Fung, and Ariel Garten combined EEG and electrocardiogram (ECG) data to create an experimental music installation where the musical content generated was determined by the relativity of the EEG and ECG signals of multiple participants.[15] There are however many non-musical applications of biofeedback such as ECG, skin resistance, and electromyography (EMG) data; ECG and EMG have many common medical applications and galvanic skin resistance is one of the main measurements used to perform polygraph tests, among other uses. Application and research of these types of data for artistic or musical creation however are rather limited; "a review of the literature shows that, EMG applications in the arts tend to fall into only three broad categories: skill analysis descriptions and establishment of norms, training method evaluations, biofeedback in both pedagogy and injury remediation."[16]

2.2 Ableton & Max

Ableton Live is one of the most popular digital audio workstations (DAW) currently available, and is unique in that it contains a version of the programming software MaxMSP, and is the only DAW that allows for seamless programming integration.[17] This therefore makes this an ideal platform in which to develop tools to connect biofeedback with music and music

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[15] James Fung, Steve Mann, and Ariel Garten, "DECONcert: Making Waves with Water, EEG, and Music," (CMMR 2007, 2008), 487–505, http://wearcam.org/icmc2007/Making_Waves_with_Water_EEG_and_Music.pdf.

[16] Gongbing Shan and Peter Visentin, "EMG Applications in Studies of Arts," in Applications of EMG in Clinical and Sports Medicine, ed. Catriona Steele (InTech, 2012), 201–8, https://pdfs.semanticscholar.org/71d6/e3113fbc05eb0d97859d7de68b48358e44ff.pdf.

[17] Mark Mulligan, "Creator Tools | the Music Industry's New Top of Funnel" (MIDIA, November 2020).

generation. To date, several projects have used MaxMSP for programming, experimentation, and sound generation of biofeedback signals, though none have been integrated into Ableton Live, which will be essential for creating a system with greater adaptability and ease of use for non-programmers.[18]

2.3 Machine Learning

Machine learning, a key component of artificial intelligence, is a powerful programming tool that, with the continued development of processing power, is able to allow computers to spot patterns and classify complex data. Certain generative machine learning algorithms can also be used to create new and original data, using previously analyzed data as a guide.

2.3.1 Weka & Wekinator

A few different machine learning software libraries were explored for biofeedback classification on this project, but based on similar existing artistic BCI and biofeedback projects, Wekinator had the best mix of speed, flexibility, and end-user accessibility. Built upon the Weka environment, a machine learning platform developed at the University of Waikato, "Wekinator allows users to build new interactive systems by demonstrating human actions and computer responses."[19] The software builds machine learning models based upon incoming OSC data, and the result of the model's classification is then routed out of Wekinator, also in the form of OSC

[18] Yian Hwang, "Composition," pcm.peabody.jhu.edu, 2018, https://pcm.peabody.jhu.edu/~yhwang9/tracings/composition.html.

[19] Rebecca Fiebrink, "Wekinator | Software for Real-Time, Interactive Machine Learning," Wekinator.org, 2021, http://www.wekinator.org.

data. Wekinator contains several different types of machine learning algorithms, a wide array of options for data processing and routing configurations, and a user-friendly GUI.

2.3.2 Piano Genie & Magenta

Machine learning can also be used for data generation in addition to data classification. The Magenta library is "an open source research project exploring the role of machine learning as a tool in the creative process."[20] It is distributed as both a Python library and a JavaScript API and, "includes utilities for manipulating source data (primarily music and images), using this data to train machine learning models, and finally generating new content from these models."[21]

3. Description

3.1 Methodology

3.1.1 Biofeedback Collection

Data collection for this project has been largely carried out using the OpenBCI 8-channel Cyton board. The Cyton Board transfers data via Bluetooth to a USB dongle containing a FTDI USB<>Serial converter, which appears to the computer as a serial port in 8-N-1 configuration, with a rate of 115200.[22] In most cases, the data is then accessed in the OpenBCI GUI, an open source Processing application developed by OpenBCI which allows the user to filter, condition, and route the incoming biofeedback data. The OpenBCI GUI also allows the user to visualize the

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[20] Google AI, "Magenta," Magenta (Google AI, 2020), https://magenta.tensorflow.org/.

[21] Ibid

[22] OpenBCI, "Cyton Data Format · OpenBCI Documentation," openbci.github.io, accessed November 30, 2020, https://docs.openbci.com/docs/02Cyton/CytonDataFormat.

incoming data in a number of ways, which allows for real-time monitoring and troubleshooting (see Figure 1).

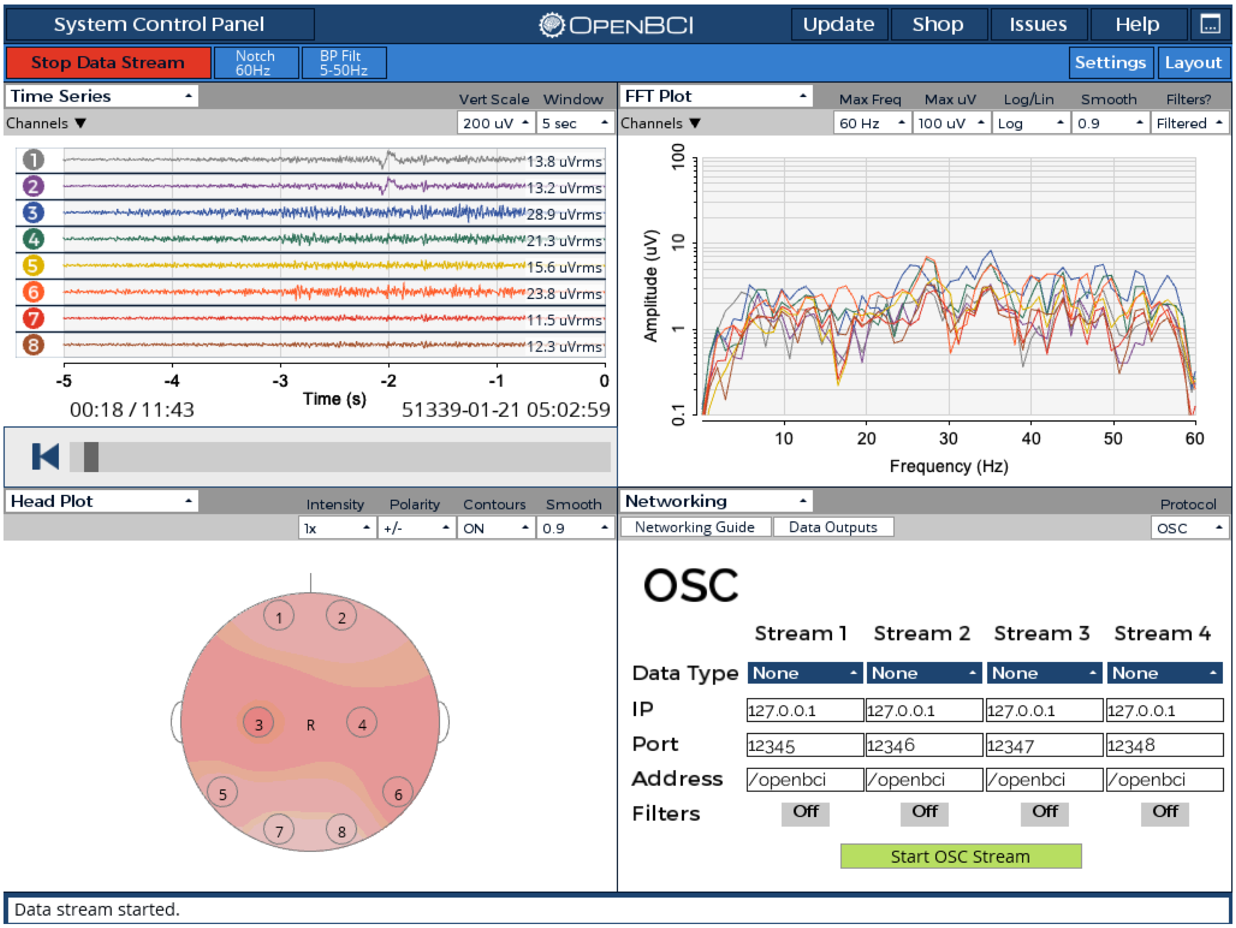

Figure 1: OpenBCI GUI

One of the primary uses for the OpenBCI GUI is as a means of monitoring data collected from the OpenBCI Cyton board and distributing this data via Serial, OSC, LSL, or UDP protocols. The software includes many useful modules for monitoring the EEG activity and ensuring its validity. The Time Series module displays the real time brainwave voltage received from the EEG and alerts the user to any electrode malfunctions or irregularities (See Figure 2).

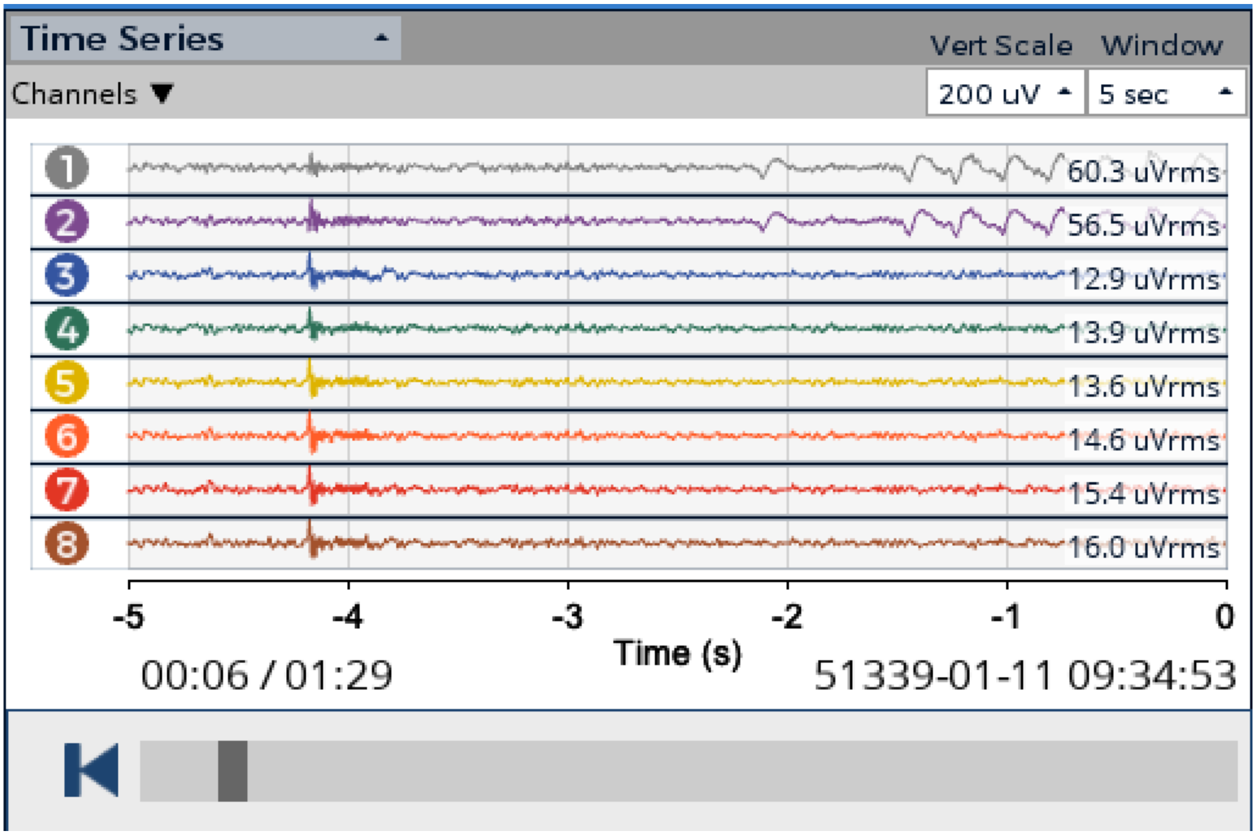

Figure 2: OpenBCI GUI Time Series Module

There is also a similar module, the Head Plot Module (see Figure 3), which uses the electrode voltage and placement to monitor brain activity in different regions of the brain.

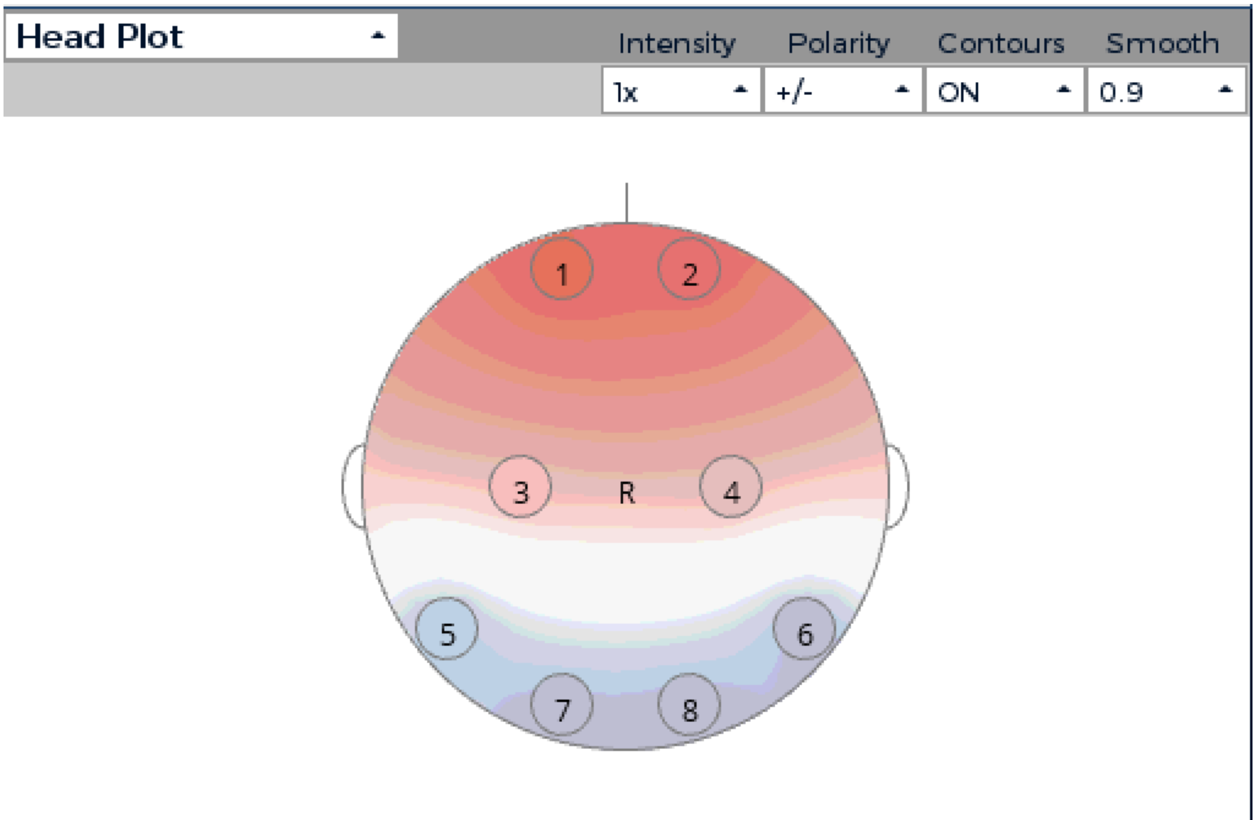

Figure 3: Head Plot Module

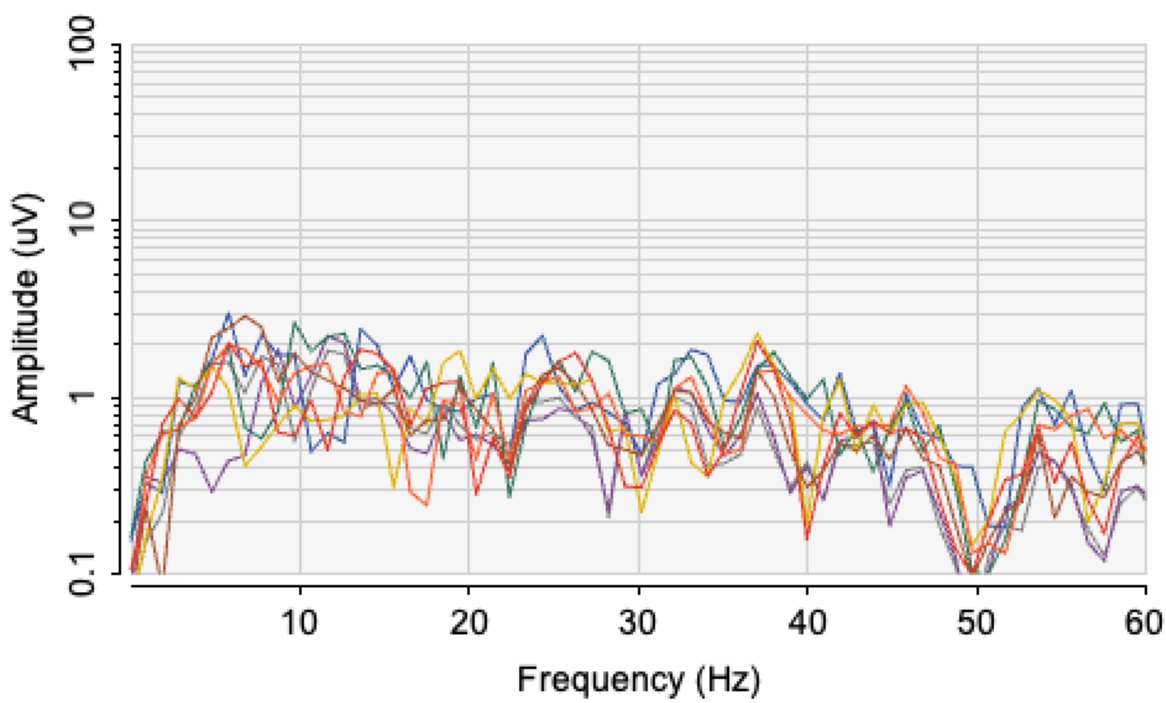

Figure 4: FFT Plot Module

The FFT Plot Module (see Figure 4) is another tool provided by the GUI which allows the user to monitor and analyze the composition of the raw EEG signals. This is useful because an FFT analysis of the raw signal allows measure the average band power of each of the five types of brainwave: Delta, Theta, Alpha, Beta, and Gamma. These average amplitudes can also be monitored using the Band Power Module (see Figure 5).

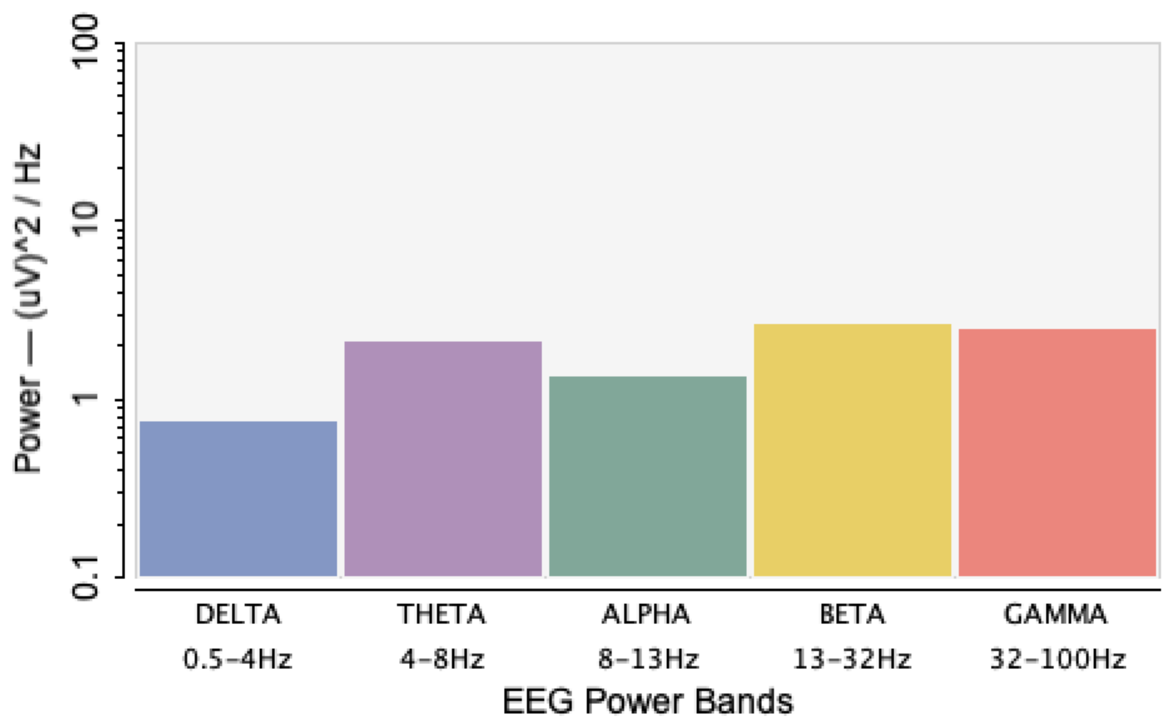

Figure 5: Band Power Module

The OpenBCI GUI also contains the EMG Module (see Figure 6), a module to monitor muscle activity of an attached electrode.

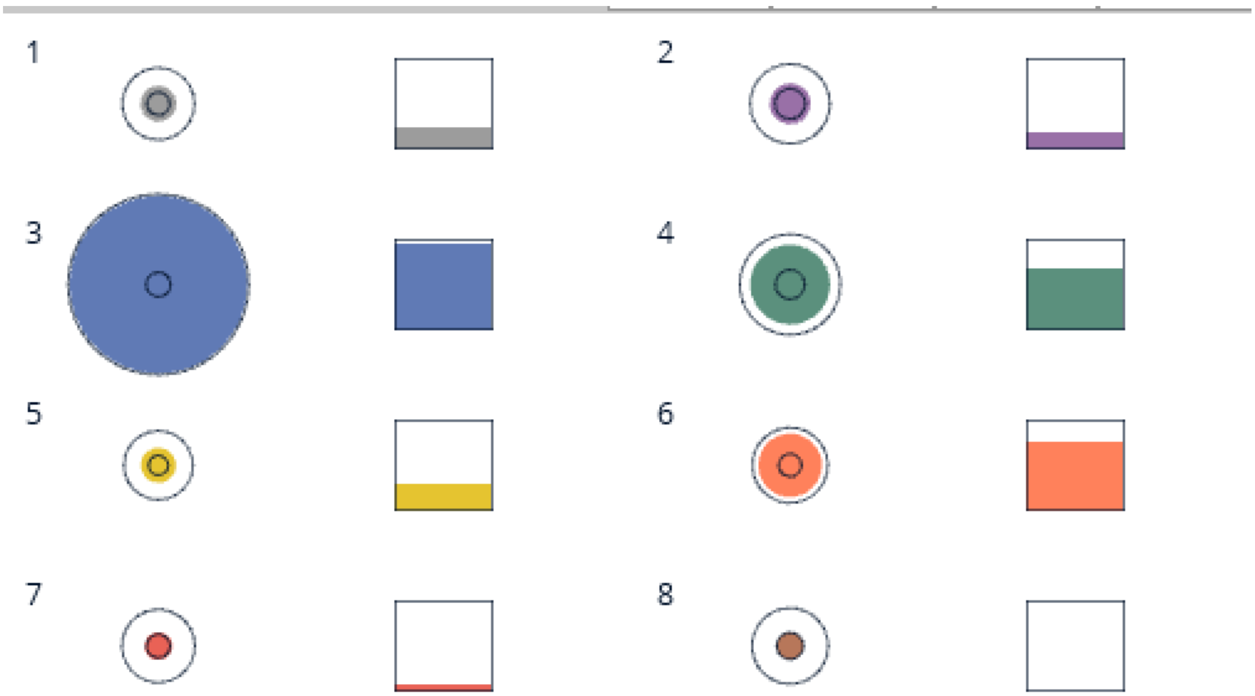

Figure 6: EMG Module

3.1.2 OSC Data Routing

All of the data that is used to animate the aforementioned biofeedback modules can be output from the OpenBCI GUI in the form of Open Sound Control (OSC) messages, which allows the data to be routed between applications or to external devices over a network. OSC is, "an open, transport-independent, message-based protocol developed for communication among computers, sound synthesizers, and other multimedia devices."[23]

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3.1.3 Machine Learning Biofeedback Classification

The machine learning classification of the biofeedback data is handled by the application Wekinator (See Figure 7). Wekinator takes the Biofeedback signals as an input, attempts to classify them using a neural network, and sends an outgoing OSC message back to the Max plugin.

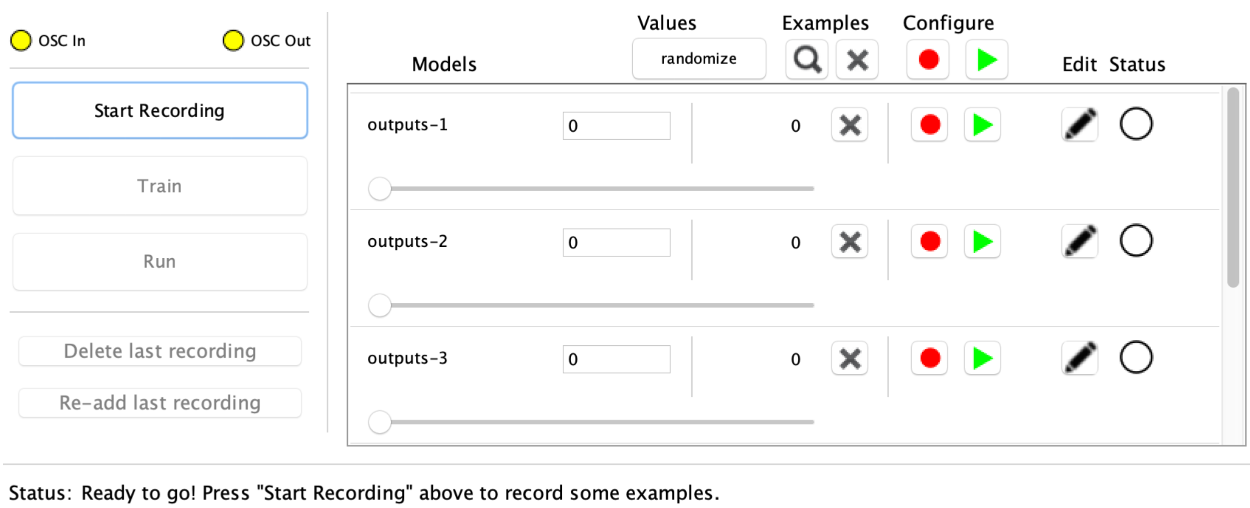


Figure 7: Wekinator Machine Learning Application

3.1.4 Generative Machine Learning for MIDI

The Magenta library has made many generative AI music applications possible. One of the most successful applications for real time AI-assisted MIDI generation is Piano Genie, created by Chris Donahue, Ian Simon, and Sander Dieleman. Originally conceived as, "an intelligent controller which allows non-musicians to improvise on the piano,"[24] Piano Genie allows the user to create novel musical phrases and improvisations on an 88-key piano by simply

[24] Chris Donahue, Ian Simon, and Sander Dieleman, "Piano Genie," *Proceedings of the 24th International Conference on Intelligent User Interfaces*, March 17, 2019, https://arxiv.org/pdf/1810.05246.pdf.

playing one of the eight available buttons. Piano Genie uses LSTM recurrent neural networks for encoding and decoding MIDI data and has been trained, "on the Piano-e-Competition data, which contains around 1400 performances by skilled pianists."[25]

3.2 Software

3.2.1 EEG Electrode Voltage Mapper

The Electrode Voltage Mapper allows the averaged (RMS) voltage level from each of the eight electrodes to be mapped to compatible parameters within Ableton. The user can customize the maximum bounds for the voltage scaling, and can apply smoothing before and after the RMS calculation. There are also color coded voltage meters (which correspond to the voltage monitor found in the OpenBCI GUI) which allow the user to monitor the data after scaling and smoothing. And finally, accompanying the map buttons are controls for adjusting the range of the mapped output values.

Figure 8: EEG Electrode Voltage Mapper

[25] Chris Donahue, Ian Simon, and Sander Dieleman, "Piano Genie," *Proceedings of the 24th International Conference on Intelligent User Interfaces*, March 17, 2019, https://arxiv.org/pdf/1810.05246.pdf.

3.2.2 EMG Mapper

In an alternate configuration, the Cyton board can be used to record Electromyography (EMG) activity. The EMG sensors are attached to any muscle(s) and the level of muscle tension is recorded by the board, which allows for customizable gestural and physical control of Ableton. The module's layout and controls are very similar to the EEG Voltage Mapper, though the data scaling, smoothing, and internal processing have been modified to handle EMG readings.

Figure 9: EMG Mapper

3.2.3 EEG Band Power Mapper

This module allows the user to map the band power levels, which are the average amplitudes of the frequency ranges that correspond to the different types of brainwaves (Delta, Theta, Alpha, Beta, and Gamma), derived from the FFT analysis of the raw electrode voltage. The user is able to select one of five types of brainwaves and map its band power value to any compatible parameter in Ableton. There are also setting that allow the user to adjust the range of output values that the band power values will be scaled to as well as smoothing control for the incoming band power values.

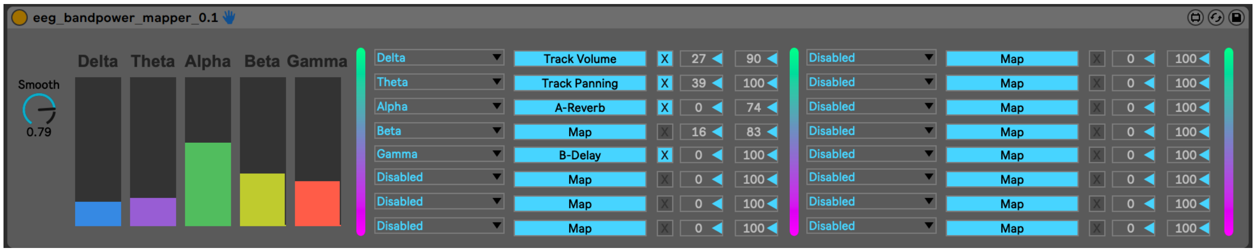


Figure 10: EEG Band Power Mapper

3.2.4 EEG Band Power LFO Generator

Similarly, this module will apply the average brainwave band power amplitude to control the frequency of a set of five low frequency oscillators that have correspond to the frequency range of each type of brainwave. So for example, alpha brainwaves occur between 8 and 12 hertz, so the alpha LFO generator is restricted to the range, with 8 being the minimum and 12 the maximum. There are five LFO waveforms that can be chosen and combined with each other: sine wave, triangle wave, sawtooth wave, square wave, and random value. Additionally, there are options for further restricting the frequency bounds, down-sampling the waveform, controlling the LFO amplitude, exponentially scaling the input band power level, and controlling the duty cycle of the triangle and square waves or the phase of the sine wave. Then, the resulting waveform, who's speed is still being controlled by the EEG Band Power averages in real time, can be mapped to any compatible parameter within Ableton.

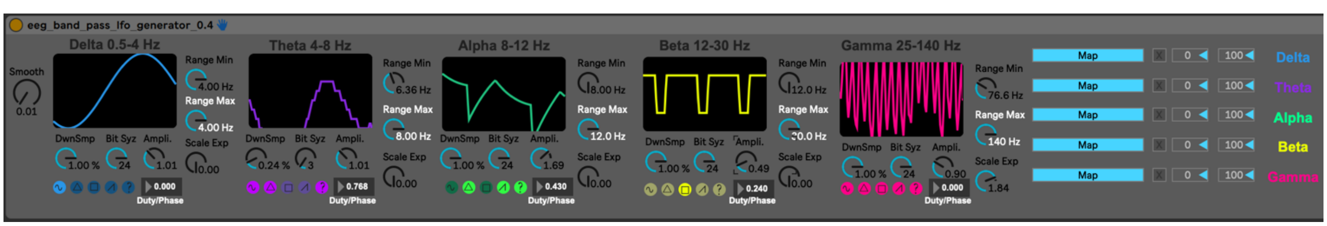


Figure 11: EEG Band Power LFO Generator

3.2.5 EEG Voltage Additive Synthesizer

This synthesizer module contains an additive synthesizer in which the partials of a given fundamental frequency (determined via MIDI input) are created by multiplying the fundamental frequency by the scaled voltage recorded from the EEG. There are partials, corresponding to the eight electrodes on the EEG. The 8 partials and fundamental are then summed together. This synthesizer was designed for direct sonification of the raw EEG voltage and is therefore highly random in nature. This module features a transpose dial, fundamental gain control, as well as smoothing control and gain control for all 8 partials. The user is given the option selecting different (and multiple) waveforms for each of the partials and fundamental frequency (sine, triangle, square, sawtooth, random) via a button matrix. And finally, the user is able to monitor the resultant waveform using the provided spectroscope and oscilloscope.

Figure 12: EEG Voltage Additive Synthesizer

3.2.6 EEG FFT Wavetable Synthesizer

This module contains an 8 oscillator wavetable synthesizer where each oscillator contains a basic waveform shape (sine, triangle, sawtooth, square, or random), which is then augmented by harmonic overtones derived from the FFT of the EEG electrode signal. Each wavetable is constantly evolving, read and processed directly from the Cyton board and OpenBCI GUI. In this way, the resulting synthesizer generation is a full spectrum timbral sonification of the full range of recordable brainwave activity (0.5hz to 125hz). Each oscillator contains independent controls for gain, tuning (both with semitones and cents), duty cycle (where applicable), and a dropdown menu to select the initial waveform. There is then a global envelope control, master gain slider, and scope for the final output. The EEG FFT wavetable sonification affects only the timbre, and so the fundamental pitch of the oscillators are effectively controlled via MIDI input or by altering the semitone or cents adjustment dials.

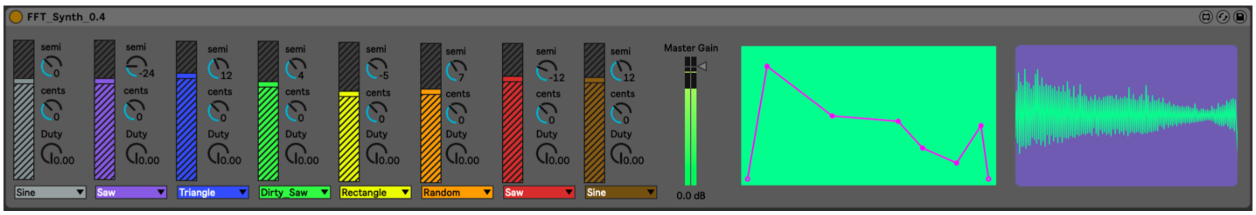


Figure 13: EEG FFT Wavetable Synthesizer

3.2.7 Wekinator OSC Router

This module allows the user to route the various types of incoming OSC data from the OpenBCI Cyton board, applying smoothing if so desired, specify OSC ports and monitor activity, and send to Wekinator for machine learning classification. Smoothing is often helpful for training machine learning models as it can help reduce noise and erratic performance. Using the dropdown menu, the module also sends Wekinator initialization commands via OSC to prepare Wekinator for various configurations. Though this version has been designed to work specifically with an OpenBCI Cyton board as an source and Wekinator and the Wekinator Input Helper as a destination, but could easily adapted to work with other sources and destinations.

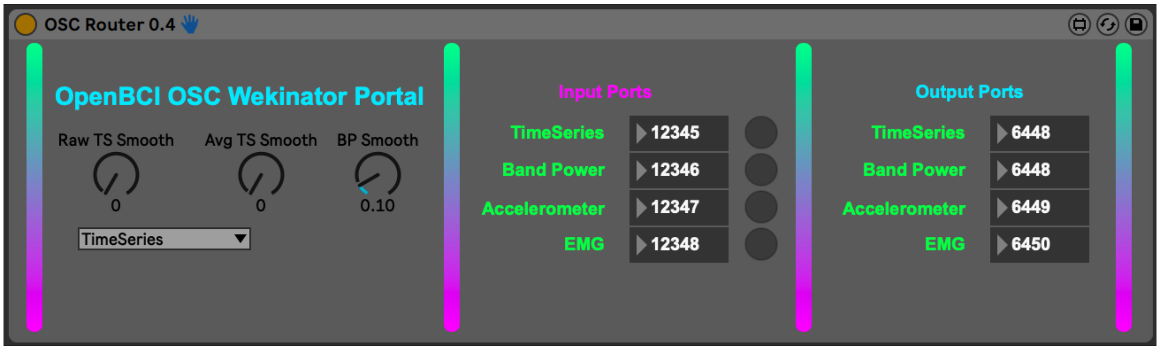


Figure 14: Wekinator OSC Router

3.2.8 Wekinator OSC Receiver

After the Cyton board biofeedback data is sent to Wekinator for machine learning classification and/or gesture recognition, this module will then receive the machine learning output(s) sent back from Wekinator and allow them to be mapped to compatible parameters throughout Ableton. There are also controls for modifying the OSC port, applying smoothing, and adjusting the minimum and maximum mapping values. In a case where multiple OSC messages are being sent from Wekinator, additional instances of this Max4Live module can be used.

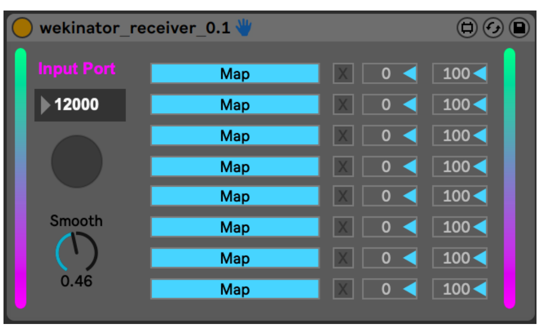


Figure 15: Wekinator OSC Receiver

3.2.9 Max4Live Genie

The Max4Live Genie module is a modified, Ableton compatible version of Piano Genie which syncs with Ableton's tempo and transport controls to notes autonomously, with controllable parameters such as scale, tempo, and temperature. The temperature parameter controls interval probability of the MIDI output, where higher values increase the probability of larger intervals between successive generated notes. Scales can selected from a dropdown menu or controlled via a probability based dial. In the case, the diatonic modes have been used and ordered from 'saddest' (Locrian) to 'happiest' (Lydian), though it is possible to customize the available scales and their order in the probability dial. Combined with the aforementioned mappable modules (Electrode Voltage Mapper, Band Power Mapper, LFO Generator, EMG Mapper, or Wekinator OSC Receiver), the Max4Live Genie will allow the user to use the biofeedback data collected from the Cyton board to control several elements of the autonomous AI MIDI generator, and the flexibility to create custom configurations using the large variety of available mapping possibilities.

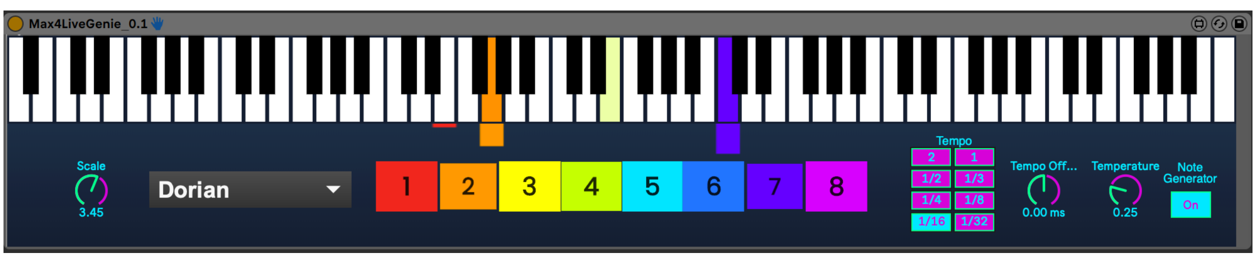


Figure 16: Max4Live Genie

4. Innovative Aspects

4.1 Synthesizer Sonification of EEG Signals

This project contains two Max For Live plugins which allow the EEG signals to be sonified directly. One plugin contains a nine-oscillator additive synthesizer and allows the frequency and amplitude of the overtone oscillators to be controlled by EEG electrode signals, and the second plugin contains an eight-oscillator wavetable synthesizer in which each of the eight oscillators' timbres are derived from the FFT of the EEG electrode signals.

4.2 Neural Network Classification of Biofeedback Signals

In order to make sense of the often noisy data collected from biofeedback sensors, this project uses neural networks, a type of machine learning algorithm, in addition to smoothing algorithms, which allows for meaningful classification of the signals and greater usability.

4.3 Biofeedback Control of MIDI CC and DAWs

Biofeedback has been used extensively in the fields of medicine, neuroscience, meditation, and many others, but its use as a control source of MIDI CC values (which allows it control parameters within a DAW or virtually any MIDI compatible device or software) is a unique use of this technology.

4.4 Biofeedback Control of Generative Machine Learning

In order to allow for music creation using only biofeedback signals, this project links the biofeedback control derived from the neural network classifications to control the way in which a generative machine learning model creates melodic content.

5. New Skills Acquired

5.1 Programming

The vast majority of this project was programmed using Max 8 (also known as Max For Live when operating within Ableton), a visual programming language. Other programming languages also needed to be used for various other parts of the system, including Processing, Java, TensorFlow, Python, and JavaScript. Knowledge of OSC and MIDI routing was also essential in connecting disparate hardware and application

5.2 Machine Learning

In addition to learning the Python and Java code required, it was necessary to understand the overarching concepts of machine learning in order to run and implement correctly. There exists a variety of different machine learning algorithms, each better or worse suited for different tasks and input data. Additionally, within each machine learning algorithms, there are other algorithms and parameters that can be adjusted in order to achieve better results. Understanding the theory and meaning behind all of these components was crucial to implementing machine learning as part of this project.

5.3 Neuroscience

In addition to understanding how to make the data easier for the computer to process, a knowledge basic neuroscience was required in order to design the software and machine learning in a way that could create the meaningful experience for the user. Learning about the different types of brainwaves and overall architecture of the human brain was an important step in this project's planning and design phase.

5.4 Sound Design

Programming the synthesizer modules required a complete understanding of the principles behind additive and wavetable synthesis, and how those concepts could be implemented in Max.

6. Challenges

6.1 EEGs and Brainwaves

Working with EEGs and Brainwave data can have significant challenges related to noise and interreference. The electrodes on the EEG are very sensitive and prone to interference. Movement by the user and outside electronic interreference (a notch filter is always at either 50 Hz or 60 Hz to remove interference cause by modern AC power in buildings) can add considerable noise to the EEG signal. It can also be difficult to adjust the positions of the electrodes for different users.

6.2 Machine Learning

Machine learning with this noisy data can also be challenging. The greater the signal noise, the less accurate the machine learning models will be. Even with reliable readings, there are limits to what sort classifications machine learning can effectively make using brainwaves; it is not able to identify complex thoughts but rather basic neurological states (such a focused versus unfocused mind). It can also be very difficult for the user to accurately change neurological states concretely and in a way that allows it to be distinguishable for a machine learning program.

Even when all of the aforementioned problems have been mitigated, machine learning can be a very CPU heavy process, scaling with model complexity, and training times can be non-trivial. In addition to long processing times, some of the more complex algorithms that were tested on the EEG data suffered from over-fitting, which is when a machine learning model's analysis becomes too heavily correlated to the training data set, making it unable to accurately classify the new data.

6.3 Routing, Networking, and Application Integration

OSC routing, especially when using multiple, large data streams, can also pose problems for the CPU and are subject to bottlenecks when connecting several different programs together simultaneously. There were other logistical problems that arose while using several different applications and pieces of hardware together.

7. Future Plans

A lofty, futuristic goal for this project would be a system that allows a user to think music into existence. Such a system however is likely many years away; according to neuroscientist and musician Dr. Thomas Deuel, it remains impossible to, "just look at an EEG of your brain and say 'you're thinking about E sharp'…we're not even close to that".[26] This project however

[26] Microsoft Research, "Studio99 Presents: Thomas Deuel and His Encephalophone," Posted on June 27, 2016, YouTube Video 58:04 https://www.youtube.com/watch?v=Ad2UmTv33DU.

represents a small step in that direction, and can continue to be built upon as technology and understanding continually progresses. There are several other forms of biofeedback that could also be integrated into this system to hypothetically improve the performance of this system.

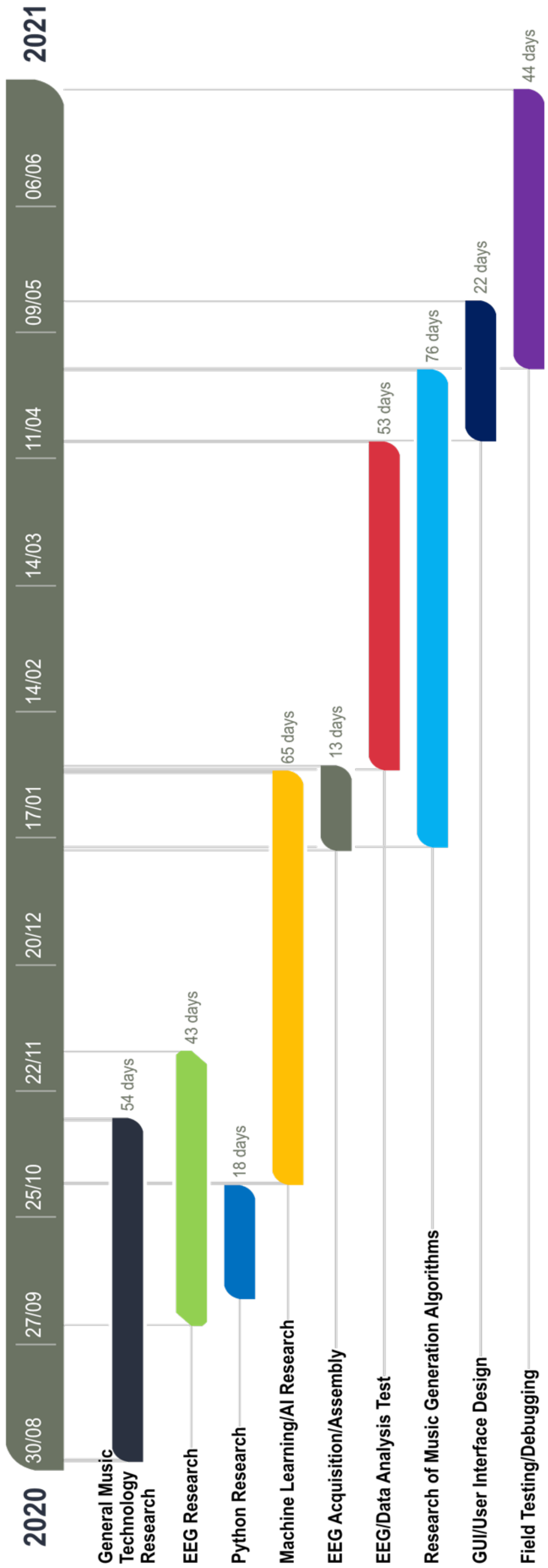
One of the stated goals of this project was to create a system that would allow people who could not afford to attain high musical proficiency an opportunity to create music in a meaningful way. However, this system as tested required thousands of dollars' worth of software and hardware to operate. An important consideration for future development then is to adapt these concepts and algorithms for a less expensive system using open source software (rewriting the software in PureData, an open source visual programming language similar to Max, or C++), low-cost microcontrollers (such as a Raspberry Pi or an Arduino), and affordable biofeedback sensors.

And finally, many technical and usability issues arose in this project because of the amount of disparate applications being used simultaneously. Future development should focus on creating a unified GUI that houses bespoke adaptations of the other open-source applications (OpenBCI GUI, Wekinator, TensorFlow and PureData and/or C++ routing and processing).

8. Conclusion

With advances biosensing and computing technology a forgone conclusion, researchers, musicians, and music technologist can begin to think about the new and exciting way that this technology can be used to create the future of music. This experimental project and with room to improve, become more elegant, and simplify, represents a proof of concept of how human can continue to narrow the divide between musical thought and musical creation. This project also demonstrates how artificial intelligence, rather than replacing human musical creation, can be seen as more of a creative collaborator, enriching the possibilities of musical instrument and composition overall. And hopefully, these new avenues of exploration can help flatten the learning curve of music creation and production.

Appendix A. Timeline



Appendix B. Resources and Budget

ITEM						
EXPENSE	**PROPOSE D**	**REA L**	**AFTER 1 MONTH**	**AFTER 2 MONTHS**	**AFTER 5 MONTHS**	**TOTAL**
MATERIALS (DISPOSABLES)						
MISC ELECTRONIC ACCESORIES	$50	$0	$0	$0	$0	**$0**
MATERIALS SUBTOTAL	**$50**	**$0**	**$0**	**$0**	**$0**	**$0**
EQUIPMENT						
HARDWARE						
OPENBCI EEG	$850	$0	$0	$0	$0	**$0**
ADAFRUIT PULSE SENSOR AMPED	$25	$25	$25	$25	$25	**$25**
ARDUINO LEONARDO	$20	$0	$0	$0	$0	**$0**
SOFTWARE						
MAXMSP	$200	$0	$0	$0	$0	**$0**
ABLETON LIVE 10 SUITE	$450	$0	$0	$0	$0	**$0**
EQUIPMENT SUBTOTAL	**$1545**	**$25**	**$25**	**$25**	**$25**	**$25**
SERVICES						
3D PRINTING	$250	$0	$0	$0	$0	**$0**
SERVICES SUBTOTAL	**$250**	**$0**	**$0**	**$0**	**$0**	**$0**
FEES						
OWN FEES						
EEG ASSEMBLY	$200	$0	$0	$0	$0	**$0**
EEG CLASSIFICATION RESEARCH AND DEVELOPMENT	$5000	$0	$0	$0	$0	**$0**
AI MUSIC GENERATION RESEARCH AND DEVELOPMENT	$3000	$0	$0	$0	$0	**$0**
GUI PROGRAMMING	$1000	$0	$0	$0	$0	**$0**
SYSTEM TESTING AND DEBUGGING	$2000	$0	$0	$0	$0	**$0**
FEES SUBTOTAL	**$11500**	**$0**	**$0**	**$0**	**$0**	**$0**
TOTALS	**$13355**	**$225**	**$225**	**$225**	**$225**	**$225**

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