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Pierre-Henri Vulliard

► **To cite this version:**

Pierre-Henri Vulliard. Music from Aura: Music Generation using EEG and Kirlian Photography for Temporal Difference Learning. Journées d'Informatique Musicale (JIM 2018), May 2018, Amiens, France. , 2018. hal-01791480

**HAL Id: hal-01791480**

**<https://hal.science/hal-01791480>**

Submitted on 14 May 2018

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# MUSIC FROM AURA: MUSIC GENERATION USING EEG AND KIRLIAN PHOTOGRAPHY FOR TEMPORAL DIFFERENCE LEARNING

Pierre-Henri Vulliard  
SCRIME/LaBRI  
pierre-henri.vulliard@u-bordeaux.fr

## ABSTRACT

Our aim is to fill the gap between computer music and musical emotions. We use a 2D emotional space (2D ES) both to analyze listener's emotions captured from physiological measure and to drive a music generator with a Reinforcement Learning algorithm. We present hereafter the Reinforcement Learning algorithm and the different parts of our framework used as input (emotions classification with Emotiv EEG headset and Kirlian photography device, to improve the machine learning by using data that have no correlation between them), and output of the algorithm (rhythm and scale/chords generation). Some current and future applications are also briefly depicted.

## 1. INTRODUCTION

*How to represent emotions both in music and in brainwaves analysis:* The most used model is the representation of emotions in 2D valence/arousal space, where valence represents the way one judges a situation, from unpleasant to pleasant and arousal expresses the degree of excitement felt by people, from calm to exciting [1].

*Emotions as a model for the interaction between brainwaves and music:* Numbers of experimentations have been pursued for the sonification of brainwaves. However, the fuzzy aspect of both music and emotions spaces makes traditional algorithms inefficient. Thus we choose for this experiment two more appropriate algorithm from Reinforcement Learning family, QLearning and Sarsa( $\lambda$ ) [2]. One characteristic of our work is to include machine learning tools with a great symmetry between its inputs (listener's emotions captation from his brainwaves analysis) and its outputs (music generation based on emotionally connoted parameters). From an algorithmic point of view, this symmetry has no particular meaning; but beyond a purely artistic approach, it should create conditions for a retroactive loop, it is widely admitted that music has an undisputable influence upon listener's mood and emotion, and numerous studies have adressed its effect [3, 4].

## 2. REINFORCEMENT LEARNING

### 2.1. Reinforcement Learning features

Reinforcement learning (RL) is learning by interactions with the environment. Its aim is, roughly speaking to map situations to actions in order to maximize a numerical reward signal. Clearly, a learning agent must be able to sense the state of the environment and to take actions that affect this state, and it also needs a goal to achieve. Temporal difference learning (TD) is a combination of Monte Carlo approach and Dynamic Programming. As for the Monte Carlo approach, TD can learn directly from the experiment (no need of a model of the environment dynamics), and as for the Dynamic Programming approach, TD updates its estimate based on prior estimation without waiting the end of the experiment and the final outcome.

### 2.2. Interest of Reinforcement Learning for music

*Bio-mimetism:* Reinforcement Learning methods take their insight from animal psychology studies, like those analyzing how an animal can learn from trial and error to adapt to its environment, or those based upon language learning.

They are from the family human-like algorithms, and so seem well adapted to musical language learning.

*Ways emphasis vs single target:* One of the special features of the algorithm is that, in addition to the final target (tonic for tonal resolution), it also takes into account paths (harmonic walks).

*Early effectiveness:* Reinforcement learning differs from standard supervised learning in that correct input/output pairs are never presented, so it does not need prior calibration, and can be effective since early bars of music.

*Short or long term optimisation:* One of the properties of the RL approach is the trade-off between exploration (of uncharted territory) and exploitation (of current knowledge). This is a way of optimising for a fast result or for a long term optimised solution. *Poietic process:* Could help to describe musical rules directly from their attributes, for example using functional value of chords (dominant preparations, dissonances, resolutions) in mainstream tonal music based on tension/relaxation.

### 2.3. Reinforcement Learning in MuZICO

A module of Reinforcement Learning is implemented in MuZICO as a PureData interface using C++ functions

Following [2] a RL task can be expressed as a Markov Decision Problem (MDP) provided that we assume decisions and values to be functions of the current state only. At each discrete time  $t$ , the agent observes the environment state  $s_t$  - in our case it is the projection of EEG signal of the listener into the 2DES. It selects an action  $a_t$  - in our case the musical parameters driving the music generation. The action is performed and one step later (time  $t + 1$ ) the agent receives a reward  $r_{t+1}$  and reaches a new state, the reward is the distance between the classification of the EEG signal projected in the 2DES space and the goal to reach. The last component is the *policy*  $\pi_t$  where  $\pi_t(s, a)$  is the probability that  $a_t = a$  when  $s_t = s$  which is used to update the estimates.

Choice for the Reinforcement Learning algorithm are: five parameters (temperature, epsilon ( $\epsilon$ ), lambda ( $\lambda$ ), earningRate ( $\alpha$ ) and gamma ( $\gamma$ )), two possible policies (egreedy and softmax), two learning methods (qlearning and sarsa).

Temperature and  $\epsilon$  are parameters for the policies,  $\alpha$  is the learning rate used to update the expected reward of the states,  $0 \leq \lambda \leq 1$  is the parameter which drives the number of states updated ( $\lambda = 0$  the state updated is  $s_t$ ;  $\lambda = 1$  states  $s_0, \dots, s_t$  are updated).  $0 \leq \gamma \leq 1$  is the discount factor used to compute the long run reward, if  $\gamma = 0$ , the agent maximizes the immediate rewards.

## 3. ACTIONS

### 3.1. Muzico

The actions are changes of the generative music settings to aim a target emotion. According to [5], the musical parameters related to the valence of emotions induced by music are tonality and complexity. We propose here harmonic, rhythmic and melodic generative models, as well as a description of their parameters from the point of view of musical complexity.

These parameters, as they are used in the MuZICO environment, have either discrete or continuous values, and are either defined by adjectives (fuzzy classes) or by numerical values. For example, the spectrum of a sound can take values from "muted" to "bright", corresponding to specific energy values that are measurable in the signal and are linked to its spectral centroid. The other parameters related to energy in music are: the tempo of the music, the attack of the notes' dynamic envelope, the pitch of the notes, the number of instruments playing simultaneously, the more or less "natural" sound of the instruments, the percussive or sustained aspect of sounds, as well as the number of simultaneous notes [5].

All these parameters are characterized by bounded intervals used by MuZICO to generate music. Those values, corresponding to low and high energies induced by the music, can be fuzzy values (such as muted, bright) or in-

tervals for physical data. The parameters that have undefined units are translated by MuZICO into various units according to the algorithms used to produce the sounds (synthesis, sample playing, audio effect control). For instance one can translate the brightness of a sound by a particular setting of the modulation index in a FM synthesis algorithm, or by the control of the cutoff frequency of a low-pass filter applied to a sample player.

#### 3.1.1. Pitch scales

Usually scales are generated by an integer as interval, following Eq. 1.

$$\begin{cases} U_{n+1} &= (U_n \times \omega^{\frac{V}{\theta}} - U_0) \times \omega^{-p} \\ U_0 &= f_f \end{cases} \quad (1)$$

with  $p \in \mathbb{N}^+$  such that  $U_0 < U_{n+1} < \omega \times U_0$

where  $\omega$  is the octave ratio,  $\theta$  the divider of the octave to obtain the temperament,  $f_f$  is the root frequency of the generated scale, and  $V$  the interval seed of the scale.

We consider that the complexity of a pitch scale relies on the number of iterations needed to generate it, and on the values of the different parameters  $\omega$ ,  $\theta$ , and  $V$ . For example, taking  $\omega = 2$ ,  $\theta = 12$  (tonal occidental music). Let  $V = (7)$  (generation of the pitch scale by iterating through steps of fifths), and  $N$  be the number of iterations. This gives: the pentatonic scale or the Maj 6/9 chord for  $N = 4$ , the diatonic scale for  $N = 6$ , the chromatic scale for  $N = 11$

These scales have an increasing harmonic complexity.

Scales of different complexities can be generated by varying  $V$ :  $V = (4)$  and  $N = 2$  generate a pitch scale corresponding to an augmented chord,  $V = (3)$  and  $N = 3$  give a diminished chord,  $V = (3, 4, 4, 3)$  and  $N = 6$  give the ascending melodic minor scale.

#### 3.1.2. Rhythmic patterns

To keep a human-like style in beat generation, we model our inspiration upon the rhythms accompanying work songs during community repetitive labour, as activities in the field (threshing and winnowing) or domestic work (the pestle pounding the mortar). Each participant produces one single regular beat but the collective result is a more complex rhythm.

The rhythmic patterns are created by layering various iterative rhythmic patterns, all synchronized to the same underlying pulse, each pattern being defined by an offset from the common initial pulse and by a rhythmic density (number of pulses between two onsets in the pattern). The superimposition is done by a logical OR operation, considering the superimposed patterns as bit vectors, a value of 1 representing an onset, and a value of 0 no onset:

$$\begin{aligned} \text{density} = 0 \text{ offset} = 0 &\rightarrow 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1 \\ \text{density} = 0 \text{ offset} = 2 &\rightarrow 0\ 0\ 1\ 1\ 1\ 1\ 1\ 1 \\ \text{density} = 1 \text{ offset} = 2 &\rightarrow 0\ 0\ 1\ 0\ 1\ 0\ 1\ 0 \\ \text{density} = 3 \text{ offset} = 0 + \text{density} = 5 \text{ offset} = 3 & \\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 0 + 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0 &= 1\ 0\ 0\ 1\ 1\ 0\ 0\ 0 \end{aligned}$$

For the rhythmic complexity, we use a model based on Toussaint's complexity measure [6] or other techniques of rhythmic complexity evaluation, that assign a weight to each pulsation.

### 3.2. Generative attributed grammar

*Chords series:* In MuZICO, the chords sequences generation takes the context into account to oversee the transpositions related to the modulations. The complexity of a chord depends on several factors that we identified: the number of notes that make it up, the complexity of the scale on which it is built, the order of appearance of its notes in the building of this scale by iterations.

The complexity of a chords sequence also depends on several factors: the complexity of the chords that make it up, the number of different chords in the sequence, the harmonic complexity of the chords sequences, mainly taking into account the cadences and resolutions in the context of modern modal and tonal music, and the modulations in the context of the latter.

## 4. REWARD

Reward is calculated from Arousal and Valence axis of emotions, according to the Two-Dimensional Emotion Space (2DES) [1]. It is the distance between the current projection of the classification of the EEG to the final state at aim in the 2DES.

### 4.1. Emotions captation system

*Hardware:* As the title of the poster indicates, we use different sources for data acquisition: EEG headsets, connected watches, G.D.V (kirlian photography). Since the data is digital, the most scientific data (EEG, pulse) should make it possible to evaluate the relevance of the more fanciful data (aura, meditation analysis by Emotiv helmet). For EEG, we use an Emotiv headset for its convenience and its growing dissemination. We acquire data from the headset with the Emotiv C++ SDK, and transmit them via UDP protocol for further use.

*Software:* OpenViBE software[7], designed for Brain Computer Interface work, provides all the necessary tools we need for our experiment setup.

### 4.2. EEG Data Analysis

*Filters:* First level is managed by the Emotiv headset itself. By request to the C++ api, we receive two types of data from the sensors: on one hand, raw data on the fourteen channels, on the other hand, filtered face muscles information (EMG), i.e. bottom or upper face tensions. In OpenViBE software. EEG data channels are sorted and a first stage of band filters is applied, according to traditional brainwaves categories. Then comes the Common Spatial Pattern (CSP) filter stage, to improve the classification [8]. A CSP filter of dimension four is used for each band of brainwaves.

## 5. EXAMPLES OF APPLICATIONS

### 5.1. Short term convergence: Live Music Performing

*Saxophone and generative music:* Interactive music is used in real time in a saxophone improvisation show, (sometimes with dance and video projections).

### 5.2. Long term convergence: Relaxation, Music Therapy

Aware of the highly controversial statements coming from the alternative medicine community about audio stimulations which may help to induce relaxation, meditation, creativity and other desirable mental states, we implemented, nevertheless, some of these stimulations and synchronized them with the music beat.

The main clock of MuZICO calculates equivalences of tempo in BPM, duration of 16th notes, and difference in Hz for binaural beats. For instance, if bpm=120, the 16th note duration is 0.125 second, the isochronic sounds have a frequency of 8 HZ, and the left/right binaural beats channels are respectively raised and lowered from  $8/2 = 4\text{Hz}$ .

Some of the mostly used audio processes:

*ASMR (Autonomous Sensory Meridian Response):* Rhythmic noises and sounds used to provoke a pleasant sensation of tingling or chills in the skull or scalp, or as a sleep aid.

*Mindmachines:* Audio impulsions are generated on an independent stereo output to control flashing leds glasses to make a "brainwave synthesizer" (or "mindmachine").

*Binaural beats:* Binaural beats, or binaural tones, are auditory processing artifacts, or apparent sounds, produced by a slight difference in the frequencies perceived by each ear of the same tone.

*Isochronic sounds:* Isochronic tones are evenly spaced tones, quickly turned on & off;

## 6. CONCLUSION - FUTURE WORKS

In this poster we presented the MuZICO framework and the core learning algorithm as an attempt to fill the gap between computer music and musical emotions.

Preliminary results have shown that a musical construction can be deduced from EEG analysis and Reinforcement Learning. The difficulty which remains is to assert that the state reached in the 2DES is effectively the intended real emotional state.

Exploratory experiments of various scenarii evaluating the different parameters of the MuZICO framework (LDA, CSP, TD on-policy, TD off-policy, long run rewards such as maximum valence and maximum arousal for music shows, or maximum valence and minimum arousal for relaxation) are undergoing.

The operation of the algorithm requires a large amount of data, so we created a smartphone app called Personal Hypno Vibes for listening to music and to acquire physiological data in various use cases (meditation, self-hypnosis, tests on the aura).

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