A CHORD PROGRESSION LIBRARY FOR MEASURING EMOTIONS BY BCIs

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ABSTRACT

One of the ambitions of computational musicology consists in characterising music harmony in a symbolic system. In the context of the EU project Polifonia, we are exploring the possibility to associate EEG data to characterise harmony from a *cognitive* and *emotional* point of view. Data will be collected using a Brain Computer Interface (BCI). In a further step, we aim to train a ML classifier to automate the pattern recognition process.
To obtain the EEG characterisation, we will consider chord sequences. This choice represents *per sè* a novelty, considering that in literature mainly sounds and tracks have been explored with BCI interfaces. We present preliminary findings and on that basis sketch research hypotheses to be further developed.

1. INTRODUCTION

Polifonia[1] is an EU Horizon 2020 funded project aiming to recreate the connections between music, people, places and events from the sixteenth century to the modern-day to enhance our understanding of European musical heritage. With the help of Artificial Intelligence, Polifonia will analyse sounds, texts and musical scores to support musicologists in developing new perspectives on the history of European musical heritage. One of the objectives of the Polifonia project is to explore how AI can be ap-plied to support musicological studies. Here we focus on acquiring traces of human experiences of *harmony*.
From a cognitive point of view, it is vital to understand how harmony is processed by the brain and how the results of this processing affect the body. Emotions are a privileged way to study embodied cognition, and harmony can be thought to be a sort of symbolic means that modulates the relationship between basic embodied reactions to feelings and higher cognitive processes.
Thus, the first research question we aim to reply is related to feelings: isn't the feeling a result of the chord in relation to the reference key or are there other factors involved?
In this paper, we report on an experiment aimed at measuring by EEG the emotional reactions elicited within a collection of prototypical chord progressions. In the past, experiments have been conducted using tracks and sounds, such as for the IADS (International Affective Digitized Sounds – IADS) [1] and for musical videoclips/songs (Database for Emotion Analysis using Physiological signals – DEAP) [2]. However, to the best of our knowledge, this is the first attempt at recording EEG measurements of experiencing isolated, prototypical chord progressions.
The motivation for focusing on chord progressions rather than full pieces of music is related to the need of reducing the impact of familiarity. In fact, according to Thammasan et al. [3], music familiarity influences both the power spectra of brain-rhythms and the brain functional connectivity. Empirical results suggests that the use of only songs with low familiarity level can enhance the performance of EEG-based emotion classification. In their work, Naser and Saha [4] show the influence of music liking on EEG-based emotion recognition. It is then necessary to avoid familiarity with genre or pieces including known patterns.
Following literature and to pursue the aim of finding a general pattern within a track, we identified a set of impact factors (HTTK): (a) Harmony (chord progression); (b) Timbre (instrumentation); (c) Tempo (fast, slow, etc.); and (d) Key change. We focus here on chord progression and tempo, as detailed in the following chapter.

2. EXPERIMENTAL SETUP

To set up the experiment, we started creating a library of progressions to measure the elicited emotions, that is the same harmony with different timbre, tempo and key, combining these elements. In this way we could guarantee the non-familiarity, isolate the harmony and play with the HTTK factors fixing one of them and varying the others, obtaining, so, many combinations to experiment.

To do this, we created a library of 19 progressions selected among common ones (from: https://en.wikipedia.org/wiki/List_of_chord_progressions). The list includes well-known chord progressions from several genres of Western music, spanning from pop, blues, to classic. Chord sequences can be major, minor, or modal (e.g. mixolidian). Regarding the timbre, in this first experiment we considered only Piano. Three tempos have also been considered: 90bpm, 120bpm and 150bpm.

The library of chord progressions' midi files and the corresponding list of chord progressions can be found at (inserire link a gthub)
To include participants to the experiment, we adopted the following criteria:

- No hearing impairments
- Distributed in age and sex
- Numerosity: 10/track/experimental group

Following Bonneville-Roussy et al. [5], the chosen age ranges are: 14-20; 21-45; over 45, covering generational

[1] Polifonia Project: http://polifonia-project.eu

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trends. Participants were isolated by noise through headphones, sitting relaxed and wearing MUSE headset to collect EEG data. MUSE is an EEG-based BCI headset[1], that is a portable scalp electroencephalography (EEG) system, battery powered and provided of four active electrodes located at 10-20 coordinates TP9, AF7, AF8, and TP10.
Each participant has been submitted to the 19 stimuli in the three different bpm, played randomly and each preceded by 30 seconds of silence to record subjects' baseline.
After the experiment, a questionnaire has been also submitted to the participants, asking if they were somehow familiar with the patterns. Also, participants have been asked to report the felt emotion on arousal (calm to excited) scale. The rating has been collected by Self-Assessment Manikin (SAM) [6] where arousal ranges from 1, depicted by a relaxed, sleepy figure, to 9, an excited, wide-eyed figure.

3. PRELIMINARY RESULTS

In this first exploratory work, we focused on the analysis of the beta/theta ratio evaluation, already used in the literature to establish a subject's arousal levels. In this case, the lower the ratio, the lower the arousal, i.e. the degree of the engagement of an organism with its surroundings. A low arousal is generally associated with cognitive tasks or emotional states that do not require attentional resources.
As hypothesised, arousal is higher with time 150bpm and 120bpm across all the subjects and age-range. Particularly, arousal is higher in 120bpm for 21-45 age-range and it is higher in 150bmp both for 14-21 bpm and for over-45 age range.
We discuss our findings considering the Arousal/Valence model by Russell [7].
In the Russell's model, emotions are represented by the valence and arousal dimensions [6]. Following psychology, valence represents the attractiveness or aversion of an event or object, varying from negative to positive, indicating the level of pleasantness perceived by the individual related to an event or an item. Arousal is defined as the physiological and psychological state of being prompt to reply to a stimulus. The arousal level ranges from low (sleepy-like sate) to high (excited state) and it modulates all the organism's functions. Low arousal emotions are characterized by a disengagement tendency, since the individual does not feel the urgency to do something to change their state. The emotions can be both positive (e.g., calm) and negative (e.g., sadness). High arousal emotions, instead, call in attention resources and prepare the organism to give a response. Positive high arousal emotions (e.g., happiness) can considered the apex of a demanding process that results in a positive experience.
In this preliminary work, we first focused on the arousal values since the research is still *in fieri*. We aim at giving exact EEG values for valence, confirming our findings through the self-assessment test submitted to the participants. In fact, considering that valence is a subjective part of an emotion, it usually measured by asking the participants to the experiment to give feedback about their perception through a self-assessment test, such as SAM. Consequently, valence is usually considered only for its positive or negative value. Moreover, in literature some successful attempt to give an exact measure of valence have been performed. Consequently, we aim at applying approaches similar to those found in literature to associate to each chord progression a specific EEG value so to capture the whole emotional experience of the individual starting by the combination of arousal and valence.
We conclude with a summary of relevant findings and possible hypotheses for future research:

- We recorded a consistent increase of Arousal in relation to Tempo for the subjects in all age groups. Crucially, the results of the Theta rhythm analysis is consistent with the Beta/Theta ratio, which further support this finding. It means that Tempo may be considered a reliable modulator of one's arousal level.
- Valence appears to be consistent on the majority of chord progressions, although further research is needed to characterise the mood associated with each chord sequence.

The next step in this research is to develop a set of data visualisations that could be used by musicologists to develop explanations for the patterns that we observed in the EEG data. In addition, we aim at performing new experiments accompanying the EEG observation with survey questionnaire that may better help to related Valence/Arousal levels with EEG traces. Future work also includes reproducing the experiment with different BCI devices, in order to increase the confidence in the observations. Finally, we aim at enriching the collection of chord patterns and publish a dataset to be used as a benchmark for researching on characterising harmony via BCI-mediated observations.

4. REFERENCES

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