A Preliminary Study about the Music Influence on EEG and ECG Signals

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Abstract: In this work, music is used to elicit emotions and the impact produced by it on the electrocardiogram and electroencephalogram signals is measured. Test consists a sequence of 12 songs where each one is played during 1 minute. Songs were grouped in 4 sets based on pleasant/activation level. In this preliminary study, 6 male subjects realized the trial. Individuals scored each song using Self-Assessment Manikin (SAM) survey. Biosignal parameters were analyzed with Kruskal-Wallis test (KWT). Although the sample of the subjects on whom the test was performed is small, significant variation is observed in 3 parameters extracted from the electrocardiogram when features are grouped using SAM values from survey filled in by subjects. These parameters show an increasing of heart rate with arousal level and when songs are not totally matched with individual preferences. The use of information extracted from biosignals in therapies for individuals with low interaction is proposed for future studies.

1 INTRODUCTION

The potential of music to evoke emotions make it a valuable tool in multiple situations. One of the most interesting applications is music therapy whose goal is to increase awareness and attention, promote sensory processing, create a feeling of enjoyment and develop sense of autonomy and control (Adler et al., 2017). In (Stephenson, 2006) a paper review is done about aims and methodologies used by music therapists working with individuals with severe disabilities; music therapy sessions, when designed in collaboration with educators, may supply a framework for eliciting and practicing communication abilities. In (Bradt et al., 2013) a review is done about the effect of music in in coronary heart disease (CHD), result shows that music may have a therapeutic effect on anxiety in individuals with CHD, mainly those with a myocardial infarction; anxiety-reducing effects are greatest when people can select which music to listen to; moreover, music may improved systolic blood pressure, heart rate (HR), respiratory rate, quality of sleep and pain in persons with CHD. In another plane it can be found applications that help us to classified music according to our mood, for instance in Spotify there are list according to different emotional situations in our daily life[1]. In (Thoma et al., 2012), songs that were emotionally congruent with individual's mood were preferred, such that emotion-regulation styles affect the selection of song characterized by determinate emotions. Music plays a role in emotion that a film arise, different perspectives of this can be found in (Kuchinke et al., 2013).

There are different strategies that allow to characterize the music with respect to the emotion it arouses. One of them is the evaluation of users. In order to accomplish this it can be used two models for emotions representation: dimensional and categorical. Dimensional representations used by psychologists often employ a n-dimensional space to represent emotions (commonly 2 or 3-dimensional). The valence-arousal (V-A) representation is one of most used example of emotional space (Russell, 1980). Valence indicates positive versus negative emotion, and arousal indicates emotional intensity. The categorical model uses 6 basic emotions from which the others can be derived. Another strategy is to extract features from the audio, the parameter values can determine the kind of emotion that the music is able of eliciting.

In (Laurier et al., 2012) a mapping between musi-

[1]Accessed on April, 2018: https://open.spotify.com/view/mood-page

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cal features (tempo, mode, harmony, loudness, pitch, etc.) an emotions categories (happiness, sadness, anger, fear, tenderness) is reported, each independent parameter is presumably insufficient to decide about one emotion; on the contrary this may need a lush of musical descriptors. Many studies have demonstrated that emotions from music are not too subjective, indeed within a common culture, the responses can be greatly consonant among listeners, such that it may be possible to replicate this in machines. The goal in (Laurier et al., 2012) is built a system to assess musical emotions from a song. For this, supervised machine learning techniques are used.

Related with these concepts in (Fritz et al., 2009) a cross-cultural study is done. Two sets of subjects participated: native African population (Mafa) and Western population. Each group listened the music of the other respective culture is done. The skill to identify three basic emotion (joy, sad, fear) from Western music is investigated in experiment 1. Results show that emotions from Western songs are universally recognized (Mafa identified the three basic emotions). The second experiment analyzed pleasantness levels changes due to spectral manipulation of music in both subject sets. Several spectral features were altered, like sensory dissonance. The manipulated songs were unpreferred with respect to original versions, such that consonance and dissonance of the music may universally influence in the pleasantness level.

In (Vieillard et al., 2008) the aim is validated 56 musical extracts.The stimuli were composed with film genre music. These transmitted four emotions depending of music features (happy, sad, threat and peacefulness), so the study provides suitable material for research on emotions. In Ekman's classification sets happiness, sadness and threat as basic emotions (Ekman et al., 1972). The fourth emotion, peacefulness, was added as oppositeness to threat. These emotions can be defined in the 2-dimensional space from valence and arousal model.

In (McAdams et al., 2017) is said that " Of interest to both music psychology and music informatics from a computational point of view is the relation between the acoustic properties that give rise to the timbre at a given pitch and the perceived emotional quality of the tone. Musician and non musician listeners heard 137 tones generated at a set dynamic marking (forte) playing tones at pitch class D across each instrument's whole pitch interval and with several playing techniques for standard orchestral instruments drawn from the brass, woodwind, string, and pitched percussion families". They scored each tone on six analogical-categorical scales in terms of valence (positive/negative and pleasant/unpleasant), energy arousal (awake/tired), tension arousal (excited/calm), preference (like/dislike), and familiarity. Twenty-three audio descriptors from the "Timbre Toolbox" were processed for each audio and analyzed in two ways (Peeters et al., 2011): linear partial least squares regression and nonlinear artificial neural net modeling. These two analyses coincided in terms of the significance of various audio descriptors in revealing the emotion ratings, but some differences were found, such that, distinct acoustic properties are being suggested.

In (Soleymani et al., 2013) a dataset contains 1000 songs, each one annotated by a minimum of 10 subjects is presented, which is larger than many currently available music emotion dataset. This study supplies a dataset for music emotion recognition research and a baseline system. The dataset consists entirely of creative commons music from the Free Music Archive, which as the name suggests, can be shared freely without penalty.

The aims of (Rodà et al., 2014) are: check how music excerpt are grouped as a function of the constraints applied to the stimuli; to study which dimensions, accompanied by valence and arousal, can be employed to represent emotional features of music; to establish computable musical parameters related with those dimensions in classification activities. The uses of verbal labels to express emotions is avoided. Participant were asked to completely focused on their own feelings from musical extracts and to group that transmitted similar subjective emotions.

During recent years neuroscientific research on music-evoked emotions have increased and in (Koelsch, 2014) it can be found a recompilation of studies of brain structures involve in this. In this work is established that the emotional effects caused by music can be motivated by memory associated with music but a part of them are induced only by the music itself. In the previous works, the emotions aroused by the music were evaluated using two sources of information: on the one hand, the extraction of the musical characteristics of the audios and on the other, the testing of the users where the feeling of being causes a certain piece of music This definition can be made using either the dimensional representation of the emotions or the categorical one. One way to objectively measure the emotion desperate for music is to measure the physiological response that the hearing causes.

The objective of (Goshvarpour et al., 2016) is to propose an accurate emotion recognition methodology. To this end, a novel fusion framework based on wavelet transform, and matching pursuit (MP) algorithm is chosen. Electrocardiogram (ECG) and galvanic skin response (GSR) of 11 healthy students were collected while subjects listened to emotional music clips in (Vieillard et al., 2008), after the section, the subjects were asked to fill in the questionnaire for the evaluation of induced emotions. To describe emotions, three schemes were adopted: two-dimensional model (five classes), valence (three classes), and arousal (three classes) based emotion categories. Subsequently, the probabilistic neural network was applied to classify affective states. The experiments indicate that the MP-based fusion approach outperform the wavelet-based fusion technique or methods using only ECG or GSR indexes. Considering the proposed fusion techniques, the maximum classification rate of 99.64% and 92.31% was reached for the fusion methodology based on the MP algorithm (five classes of emotion) and wavelet-based fusion technique (three classes of valence), respectively. In (Goshvarpour et al., 2017) results are improved to 100%.

In (Wagner et al., 2005), the most important stages of a fully implemented emotion recognition system including data analysis and classification is discussed. For recording biosignals in different affective states, a music induction method is used based on four songs chosen by the users taking into account that can provoke some special memories. Four-channel biosensors are utilized to record electromyogram, electrocardiogram, skin conductivity and respiration changes. After several parameters were calculated from the raw signals. Linear discriminant function, k-nearest neighbor and multilayer perceptron were applied together with feature reduction methods. Correct classification rates of about 92% were reached for all three classifiers.

In this work, a preliminary study is carried out with two objectives. The first target is investigating if the emotions elicited by the music can be detected in the physiological signals, that is, if it is possible setting a link between physiological changes and the pleasant/agitation levels causes to listening music. For this purpose, parameters of the recorded signals will be established and an evaluation of their significance will be made. The second goal is evaluating if the background of the subject in terms of experiences, culture and preferences can influence the emotion aroused by music.

In this first evaluation, the chosen stimuli were songs not specifically composed to awaken emotions and which have been previously evaluated in terms of valency and arousal by other subjects. The evaluation is pending, making use of other types of stimuli. From songs with which the subjects are more familiar to synthesized music with certain values in the audio parameters that facilitate the elicitation of certain emotions.

Table 1: Selected songs and their affective values.

Group	File	Valence	Arousal
1	88	5.5	6.7
1	102	5.4	6.5
1	898	5.5	6.4
2	127	5.3	3
2	979	5.5	3.1
2	686	5.5	3.4
3	227	3.5	3.1
3	297	3.6	3.1
3	530	3.5	3.3
4	161	3.5	6.3
4	729	3.5	6.4
4	987	3.6	6.3

2 METHODOLOGY

The experimentations took place in a small corner, visually isolated, of 235cm of width and 140cm of depth of a room. A comfortable temperature was kept in (22–24°) with sound environment of 29 dB[2] and light lighting to reinforce subject's focus on the display (around of 217 lux[3]). Individuals were seated on a padded chair placed 120cm away from a 18.5" monitor (aspect ratio 4:3) with a resolution of 1280×1024 pixels and 32 bits of color. Monitor was aligned with individual head. Each subject was asked to attend around 18-minute session. The recording interval was split in 2 parts (figure 1): the initial rest period of 2 minutes and 12 blocks of songs. Each song's block is compounded of a initial recovery (30s), 1 minutes of audio and filling in emotional survey as soon as possible (time limitless). A black screen with a gray cross is shown in the display center during non-survey periods. Four sets of 3 songs were selected from (Soleymani et al., 2013) (figure 2 and table 1). Songs of each set have similar V-A values. Dominance values were ignored based on circumplex model of affects (Posner et al., 2005), where valence and arousal are enough to evaluate physiological changes with behavioral, cognitive activity, and development studies. On the other hand, survey periods consist in scoring valence and arousal levels of previous song in integer scale from 1 (unpleasant/deactivation) up to 9 (pleasant/activation).

[2]Measurement was done using a Samsung Galaxy S5 and Sound Meter App (available on April, 2018: https://play.google.com/store/apps/details?id=coocent.app.tools.soundmeter.noisedetector).

[3]Measurement was done using a Samsung Galaxy S5 with its hidden menu.

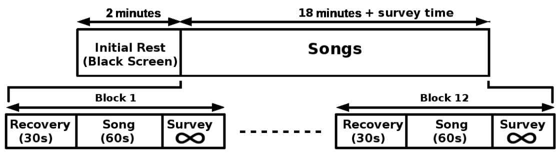

Figure 1: Test scheme.

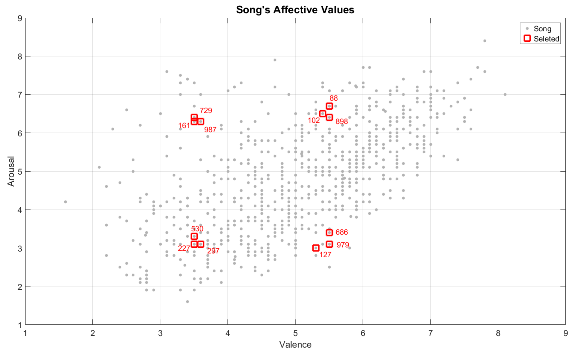

Figure 2: Selected songs and the other ones from music database.

2.1 Subjects

The trials were conducted with 6 healthy man voluntaries aged between 21 and 61 years old (average=43; standard deviation=15; no woman voluntaries).

2.2 Data Acquisition

Three different biosignals were simultaneously recorded during the tests: ECG, GSR, and electroencephalogram (EEG). The electrode locations are shown in the figure 3. The two first ones were recorded utilized Arduino UNO and an own design platform connected to Arduino (Molina et al., 2017) employed Ag/AgCl electrodes with self-adhesive/conductive gel. Arduino was programmed the library developed by (Molina-Cantero et al., 2018). Sampling rate was set to 256 Hz. ECG employed a monopolar assembly, and GSR assembly was placed on the medial phalanx of index and middle fingers. EEG was recorder from Muse device (Krigolson et al., 2017) with 220-Hz sampling rate. The ground electrode is located in Fpz, and the recorded channels were: Fp1, Fp2, TP9, and TP10. These positions are suited for the goal of this study because frontal positions are linked with positive/negative emotions(Alves et al., 2008), while temporal regions are associated auditory processing(Nunez and Srinivasan, 2006). ECG and EEG data were respectively filtered applied a hardware bandpass filter with 0.1-30 and 1-60 Hz, whereas non filter was applied to GSR data. On the other hand, EEG data must face the presence of several

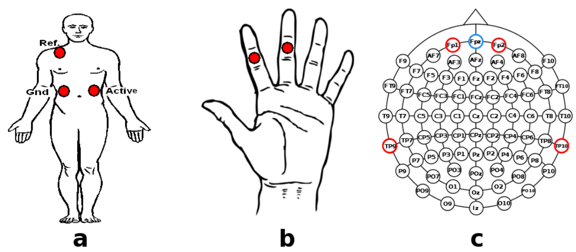

Figure 3: Electrode locations: a) ECG; b) GSR; c) EEG.

artifacts, such that environmental noise, drift, blink, saccadic eye movement, face muscle contraction, and heart rate. A bandpass filter between [0, 8)Hz and a notch filter (48, 52)Hz to reduce these problems were applied to EEG signals.

2.3 Biosignal Features

EEG signal was divided in 3 frequency bands: (8,14]Hz is α, (14,30]Hz is β, and (30, 45]Hz is γ. α wave is mainly related with occipital region with awaken, relaxation, and no-open-eye states; β rhythm is mainly linked with moderate cognitive activity in central and frontal areas; and γ band is associated with high cognitive requisites and information processing. Extracted band parameters are congregated in table 2. Normalized power of band (NPB) is the normalized power of the band, relative power (RP) means the percentage of the band with respect to the total power of EEG bands, power spectrum centroid (PSC) corresponds to spectral centroid that is the weighted mean of the frequencies present in the band, that is, the "center of mass" of this one, power spectrum deviation respect to the centroid (PSDC) is the gathering of spectrum around the PSC in the band, rather spectral deviation, and flatness (FL) means the randomness level of signal whose value is in the interval [0, 1], so that 1 corresponds to a white noise, and 0 indicates spectrum is concentrated in a small number of harmonics. Notice that value of all features is in the interval [0, 1].

The RR segments are obtained from the ECG signal through the algorithm based on lower envelope developed in (Merino et al., 2015). Different parameters are extracted from heart rate and they may be classified in two groups: information based on temporal analysis (Sörnmo and Laguna, 2005) and shape waves. The more common calculated parameters of the first group are the standard deviation of RR intervals (SDNN), the square root of the mean squared difference of successive RR segments (RMSSD),the proportion of RR intervals that differ by more than 50ms (pNN50), and the width of the minimum square difference triangular interpolation of the highest peak

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Table 2: EEG Band Parameters. $x \in \{\alpha, \beta, \gamma\}$.

Parameter	Equation
Normalized power of band (NPB)	$NPB_x = \sum_{f \in x} PSD(f)$
Relative power (RP)	$RP_x = \frac{NPB_x}{\sum_{y=\delta}^{\gamma} NPB_y}$
Power spectrum centroid (PSC)	$FC_x = \frac{\sum_{f \in x} f \cdot PSD(f)}{NPB_x}$ $I_x = max(x) - min(x)$ $PSC_x = \frac{(FC_x - min(x))}{I_x}$
Power spectrum deviation respect to the centroid (PSDC)	$NF_x(f) = \frac{(f - min(x))}{I_x}$ $DF_x(f) = PSD(f) \cdot (NF_x(f) - PSC_x)^2$ $PSDC_x = \frac{\sum_{f \in x} DF_x(f)}{NPB_x}$
Flatness (FL)	$FL_x = \frac{\prod_{f \in x} n \cdot \sqrt[n]{PSD(f)}}{NPB_x}$

of the histogram of all RR intervals (TINN). These are used to determine the variability over a short time period to obtain the influence of parasympathetic nervous system. Important information about quick random changes of heartbeat is extracted from pNN50. The second feature set are: amplitude distance between Q and S waves, Q-S time, R-Q slope, S-R slope and the kurtosis and skewness of them and RR segments. Finally, the median of RR segments (MRR) was obtained too. This measure is based on the histogram too, it is simple but not as common as the other measures based in HR.

GSR data were rejected due to saturation problems.

3 RESULTS

The outlier values were avoided in our analysis using the interquartile-range method, that is, the values out of [Q1 - 1.5(Q3 - Q1), Q3 + 1.5(Q3 - Q1)] were eliminated, where Q1 and Q3 are the lower and upper quartiles respectively.

We are interested in discovering how the biosignals features change through the different musics due to emotions elicited by them. Therefore, the KWT with 0.05 statistical significance (p-value) is applied to the parameters. Three analyses were realized. In the first one, data were grouped based on selected song sets (figure 2), that is, statistical analysis compares variations of features sorted by 4 different groups (onwards, KWT4), this means that in this analysis the subjects' particular characteristics have not been taken into account, only the music itself. We were interested in studying whether the emotion elicited by the music depends on the user's background or not, that is why the two other analyzes have been proposed. In these ones the features are categorized base on subjects' V-A values. The mean of the scores ($valence = 5.81 \pm 2.20$; $arousal = 3.03 \pm 1.96$) splits features in 2 categories: low (V1/A1) and high (V2/A2). Statistical analyses compare variations of features sorted by 2 different labels in each affective axis (onwards, KWT2V and KWT2A for valence and arousal groups respectively). Also, KWT analysis was applied between baseline and low (V1/A1) and high (V2/A2) affective groups.

The expected behavior is significant difference between groups in each analysis. However, EEG data were non significant for all KWT analysis, while ECG only three features have significant variations (figure 4): skewness of RR segments in the KWT2V analysis, and MRR and R-S slope in the KWT2A analysis. Positive skewness value indicates a bias to lower RR segment values, that is, HR is increased when a song is not totally matched with subject preferences. Similar meaning is linked with MRR. A smaller value of RR segments is associated with a higher activation, while these increase with a greater calm level. This fact coincides with a previous study focused on stress effect (Monge et al., 2014). Likewise, the significant of the R-S slope may be caused by increasing of HR when activation level is increased. On the other hand, affective groups are not significantly different with respect to baseline. Songs with a less pleasant level (V1) show a greater skewness than baseline, while more pleasantness musics (V2) draw normal distribution (similar to baseline). Also, songs with lower and higher arousal levels exhibit smaller and greater MRR values with respect to baseline, and R-S slope is smaller in A1 group ,but almost equal in A2 group. This fact may be caused by subjects' expectation about what kind of music they will be listened.

4 CONCLUSIONS

The target of this study was to analyze the variations of EEG and ECG and how these are related with subject's music preferences. The behavior of EEG features are similar in all cases, such that, none of them show significant variations, while three of ECG parameters draw variations due to song if results are grouped according to user punctuations in arousal and valence. Despite, the reduced number of subjects limit the significant of results.

In future work, the number experimental subjects of test must be increasing for getting a stronger statistical analysis. On the other hand, different musi-

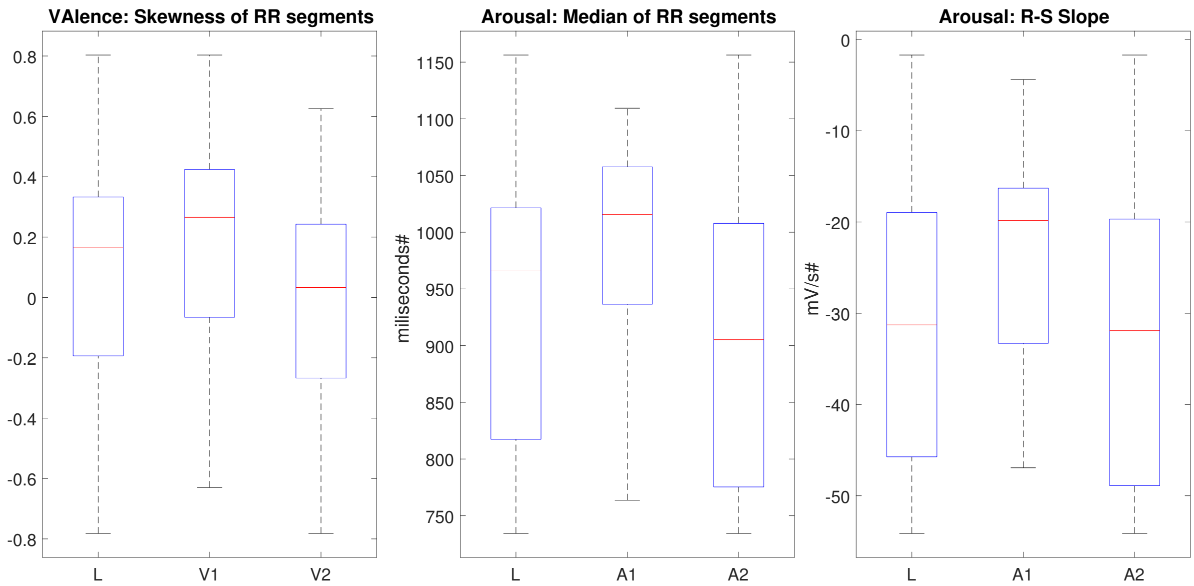

Figure 4: Boxplots of significant features from KWT statistical analyses. Left figure is the variations of skewness of RR segments; middle figure contains the changes in median of RR segments; right figure is the variations of slope of R-S wave. Symbol meanings: "L" indicates baseline, "V" identifies valence, "A" means Arousal, and numbers "1" and "2" indicate group of lowest and highest levels respectively.

cal stimulus may be employed with the objective of evaluating influence musical characteristics by themselves without considering the profile of the subject. Based on the results conducted in this work, the information provided by the physiological signals will be used to developed an adaptive music system will to improve interaction capacity of individuals with disabilities, mainly children with special needs.

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