EMOTION DETECTION FROM EEG SIGNALS: CORRELATING CEREBRAL CORTEX ACTIVITY WITH MUSIC EVOKED EMOTION

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Abstract

This master project aims to study music evoked emotion using electroencephalography (EEG) techniques. In particular, the first goal of the research is studying the correlation between EEG signal characteristics and three emotional states that are evoked by music; which are happy, sad and relax. A secondary goal of the research is correlating musical features obtained by music information retrieval (MIR) techniques with the EEG signals. An experiment was designed for proper EEG recording while subjects were listening to emotionally relevant songs. Six songs with emotional content (happy, sad and relax) were selected; three of them, were selected by us from a dataset of songs previously classified according to their emotional content by MIR techniques. The other three songs were selected by each participating subject according to their own preferences. The obtained data, EEG signals and music audio, were analyzed in order to investigate correlation among them. The EEG signals have been analyzed in order to extract features, some of them emotionally related, and these features have been used to predict the type of music to which the subject is listening. The obtained classifiers are able to predict the music type with up to 98% accuracy (base-line accuracy is 16%). The musical features were extracted in order to be correlated with the extracted EEG features. More than 10 correlations found with the correlation coefficient value greater than 0.25 and p-value smaller than 0.05.

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1. Introduction

Music's emotion evoking properties are well known for centuries [1]. From Hippocrates to al-Farabi many scientists from different eras used music for therapeutical purposes taking advantage of its relationship with emotion [2,3]. The inner mechanism of the brain how the emotions are really evoked has yet to be solved but it has been proven that music as a consequence evokes emotions [4].

Today with the devices and techniques like electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), near infrared spectroscopy (NIRS), and functional transcranial doppler sonography (fTCD) are helping us to trace changes happening in the brain and giving us opportunities to use brain as a subject for our researches [5].

In this research we use EEG technique to capture brain signals while subjects were listening to emotional evoking music in three categories: happy, sad and relax. Due to musical preferences is a subjective matter we asked to participants to pick three songs (one song for each category). Moreover we chose three songs (one song for each category) from a dataset that the songs were previously classified according to emotional states by MIR techniques which of those listened by all of the participated subjects [6]. The acquired EEG data and musical features are classified by machine learning algorithms and correlations among them are investigated.

1.1 Motivation

Decoding emotional state of a person has a variety of applications. Using EEG techniques to decode emotions provide easy facility to work in comparison to other techniques like fMRI (loud scanner noise and narrow space), NIRS (expensive and long time of implementation). The outcome of emotion decoding could be applied on brain-computer interface (BCI) applications and moreover this might be used in therapeutic manners for instance helping patients suffering from depression. There have been several approaches about EEG-based emotion detection, but there hasn't been a strong consensus about definite conclusions [7,8,9].

MIR techniques have been advanced in the past decade and pave the way for different applications. For instance, musical features extracted by MIR techniques can define mood characteristics of a song. But how these features really make alterations on our state of the mind? Studying musical features with EEG techniques could reveal some coherent attributes that music and emotion carry.

We hopefully in the end wish to contribute the previous works that had been done in these fields and the works that will be held in future.

1.2 Objectives

The study has two main objectives. On one hand to decode emotional state of a person produced by listening emotion evoking music. On the other hand to detect musical features which are relevant with EEG signals. EEG data will be gathered from Emotiv Epoc head set with its all electrodes placed on the scalp and musical features will be extracted by MIR techniques.

The project aims to predict in which emotional category subjects are listening the music and which musical features have relevant effects on subjects' EEG signal changes.

1.3 Structure of the Thesis

The rest of the paper organized as follows: Chapter 2 presents background and history about EEG system. Chapter 3 presents state of the art in EEG-based emotion classification methods. Chapter 4 presents materials and methods used in the study. Chapter 5 presents results and discussion. Chapter 6 presents conclusions. And chapter 7 presents future works.

2. Background

2.1 Early History of EEG

The EEG equipment and its applications as new technologies emerged have consistently taken advantage from them. The history of the technology that allow EEG to function could be traced back to 16th century till now but the discovery of bioelectricity, potentials and currents produced within living organisms, grounded much earlier.

2.1.1 Discovery of Bioelectricity and Electricity

The first written bioelectric event is a description of the electric catfish as a fish that "releases the troops" appeared in ancient Egyptian hieroglyph around 3100 B.C. [10]. The first written document on medical application by using electricity appeared in A.D. 46, when Scribonius Largus (Roman; c. 1-c. 50) recommended the use of torpedo fish for curing headaches [11].

The term electric was invented by William Gilbert (British; 1544-1603). He constructed a simple electroscope as seen in figure 1, a light metal needle pivoted on a pin, to measure the attractive power of amber which in Greek named as electrics (ηλεκτρον) [12]. The advancements continued in 1700's. In this period, Benjamin Franklin (American; 1706-1790), Luigi Galvani (Italian; 1737-1798), Michael Faraday (British; 1791-1867), and Jacques Arsene d'Arsonval (French; 1851-1940) were discoverers of different kinds of electricity: static electricity, direct current, induction coil shocks, and radio frequency current, respectively [13].

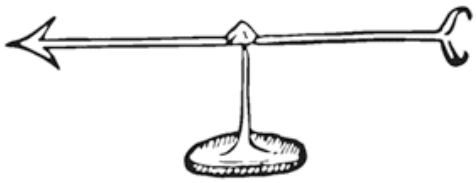


FIGURE 1. The first instrument to detect electricity, electroscope, Invented by William Gilbert (Gilbert, 1600)

2.1.2 Early Research on Bioelectrical Phenomena in Animals

A significant study about bioelectrical phenomena in animals was done by Luigi Galvani in 1791, professor of anatomy at the University of Bologna, that he caused twitches of frog leg muscles when he simultaneously touches the muscles and exposed nerves with a bimetallic arc of copper and zinc as seen in figure 2 [14]. This study is cited as the first documented experiment in neuromuscular electric stimulation, and was one of the first forays into the study of bioelectricity in animals. With the discovery of the galvanometer, which is an analog electromechanical actuator used for detecting electric current, by Hans Christian Oersted (Danish; 1777-1851) in 1820 led the way to study bioelectricity deeper. Carlo Matteucci (Italian; 1811-1865) was the first to measure the bioelectric current of muscle impulses in frog in 1838 by using the astatic galvanometer [15]. Emil Du Bois-Reymond (German; 1818-1896) began to measure biological currents in electric fish in 1840‘s by the galvanometer [16]. He also developed non-polarizable electrodes made of clay, which were used in the first animal and human EEG recordings later [17].

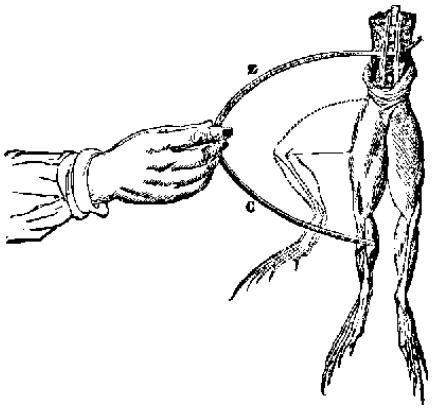


Figure 2. Stimulation experiment from Luigi Galvani (1791).

2.1.3 Discovery of EEG

In 1875, the very first demonstration on the brain's electrical activity was done by Richard Caton (British; 1842-1926). He recorded electrical activity from the exposed brains of rabbits, cats and monkeys by using mirror galvanometer [17]. He managed to observe variations associated with sleep, wakefulness, anesthesia, and death, he also identified brain areas associated with motor activity including head movement, mastication, and movement of the eyelids which were interpreted after him from his work, making him the first EEG brain mapper as well [17].

In 1913 the very first photographic recordings of EEG signals were obtained by Vladimir Pravdich-Neminsky (Russian; 1879-1952) in Kiev, he provided the first literature to show EEG with time-series waveform representation [17].

In 1920 Alexander Forbes, professor in the department of physiology at Harvard Medical School, replaced the string galvanometer with a vacuum tube to amplify EEG's electrical signal. This became the standard for EEG amplification in the following years [18].

In 1924 Hans Berger (German; 1873-1941) recorded the very first human brainwave and he coined the word electroencephalogram [17]. He also introduced the two major brain wave pattern names "alpha wave" and "beta wave", in figure 3 it can be seen. Toennies, from Institute of Brain Research in Berlin-Buch J.F, made important advancements in EEG instrumentation. In 1932, Toennies developed the first multichannel ink-writing oscillograph for recording brain potentials, and developed differential amplifier with the collaboration of B.H.C. Matthews from Physiology Laboratory, University of Cambridge, England [17]. Berger's outstanding scientific contribution didn't gain publicity worldwide until E.D. Adrian and B.H.C. Matthews verified Berger's results, they were the first ones to successfully conduct his experiment in 1934. They were able to record simultaneously and independently from different areas of the brain, revealing spatial and temporal relationships between signals. They were also successfully audified and listened the brainwaves, which was the first example of the sonification of human brainwaves for auditory display [19].

Besides the studies held in Europe in United States, Donald B. Lindsley (American; 1907-2003), co-founder of UCLA's Brain Research institute, was one of the first scientist to use the newly discovered technique of electroencephalography to record electrical brain activity [20].

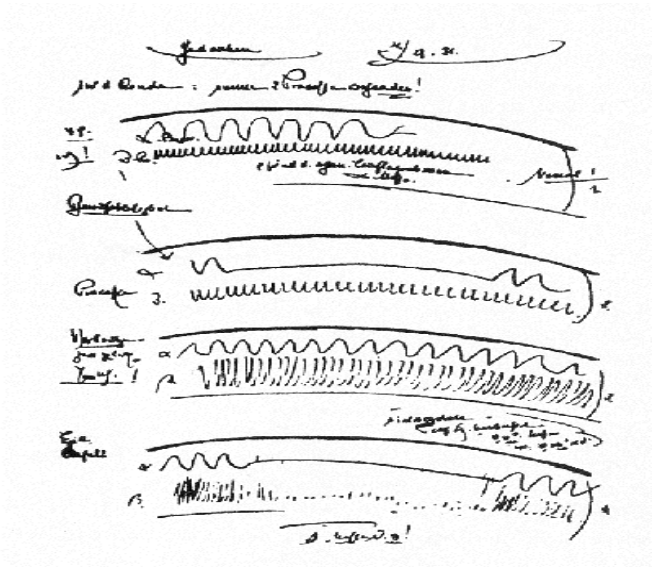


Figure 3. A page from Berger's notebook illustrating early recordings of the human EEG (1924).

2.1.4 Industrial Standardization of EEG

By the mid-1930s, commercial EEG systems were begun to appear. Many laboratories made contributions to EEG methodology and practice by using systems that were "clones" of previous designs. Albert Grass produced the first commercial EEG device; Grass Model I in 1935, which had three channels of differential amplification and an ink-writer that recorded on rolls of paper [17]. By the end of the World War II, the Model III was introduced in 1946, and had the first 8-channel and 16-channel EEGs ever made, about 5,000 systems were produced and were shipped world wide [17].

The American Electroencephalographic Society (AEEGS) was founded in 1946, the first annual meeting was held in Atlantic City NJ in 1947 with the established experimental and clinical EEGers. By the 1949 the first issue of "The EEG Journal" had been published [21].

In the 1950s first transistorized EEG amplifiers were produced by Franklin Offner, named as “Type T”, as seen in figure 4, which was a portable system that brought a new standard for EEG instrumentation with advantages of low heat dissipation, high efficiency, lower operating voltages, and small size [17]. By the mid-1950s EEG had became formal laboratory equipment in institutions and hospitals. With the introduction of digital technology EEG systems became more automated, controlled; signal storage, retrieval and numeric processing capabilities got dramatically higher.

Figure 4. First portable EEG designed by Franklin Offner (1950’s).

2.1.5 EEG with Music

In 1954, Robert Frances attempted to measure musical perception through polygraph readings, including EEG, GSR, heart rate and respiration rate while subjects listened to selected musical examples [22]. In the late 1950's, Joe Kamiya studied the phenomenon of internal perception or the awareness of private internal experiencing. He demonstrated that a subject could learn to produce alpha or beta brain states on demand [23].

In 1965, Alvin Lucier managed to generate music by using his brainwaves. He designed a performance named Music for Solo Performer, in figure 5 he can be seen in act. He achieved to map performer's alpha band to an array of percussion instruments [24,25].

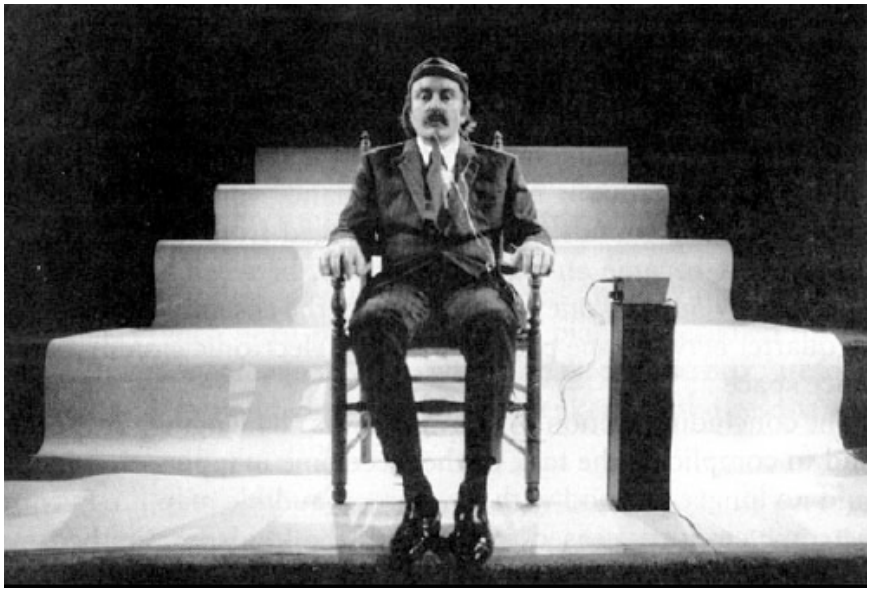


Figure 5. Alvin Lucier is performing with an EEG; He controls instruments by his thoughts (1965).

In 1967 Richard Teitelbaum, member of the innovative live electronic music group called Musica Elettronica Viva (MEV), used EEG and ECG (Electrocardiography) signals to control sources for electronic synthesizers in performances of Spacecraft. In 1968 heartbeat and breath sounds were added, which were sensed with contact microphones, to EEG signals in the creation of an electronic music texture [24]. Over the next few years, Teitelbaum continued to use EEG and other biological signals in his compositions and experiments as triggers for nascent Moog electronic synthesizers [24].

In 1970 David Rosenboom composed and performed Ecology of the Skin, in which ten live EEG performer-participants interactively generated immersive sonic/visual environments using custom-made electronic circuits [25].

In 2003 James Fung and Steve Mann designed a brainwave music concert, where a computer sensed audience reaction to generate and alter to music, reacting to their responses to the music [26].

2.2 EEG Systems and Technology

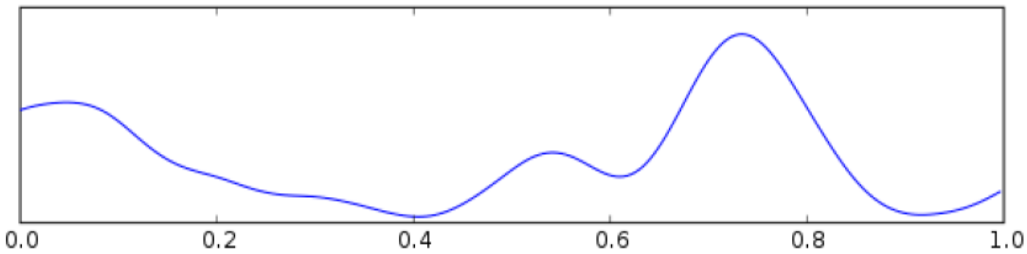
2.2.1 Electrodes and the 10-20 System

To achieve an appropriate EEG recording electrodes are placed on scalp based on internationally recognized 10-20 system. This method was developed to standardize reproducibility; Subject's studies could be compared over time and subjects could be compared to each other. An example of electrode positioning for 10-20 system for Emotiv EPOC neuroheadset can be seen in figure 7. In this system electrode locations are named to identify the lobe and numbered to identify hemisphere location. The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. Even numbers (2,4,6,8) refer to electrode positions on the right hemisphere, whereas odd numbers (1,3,5,7) refer to those on the left hemisphere. In addition, the letter codes A, Pg and Fp identify the earlobes, nasopharyngeal and frontal polar sites, respectively [27,28].

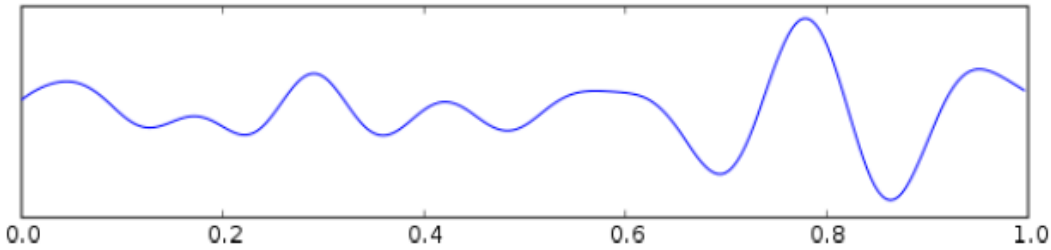
2.2.2 Important Frequency Bands

The frequency range of brain waves can be recognized from 0.5 to 500 Hz [29]. Important frequency ranges that are clinically relevant are divided in to four main group; Alpha, beta, theta and delta bands [29]. The frequency of EEG measurements ranges from 1 to 80 Hz, with amplitudes of 10 to 100 microvolts [30].

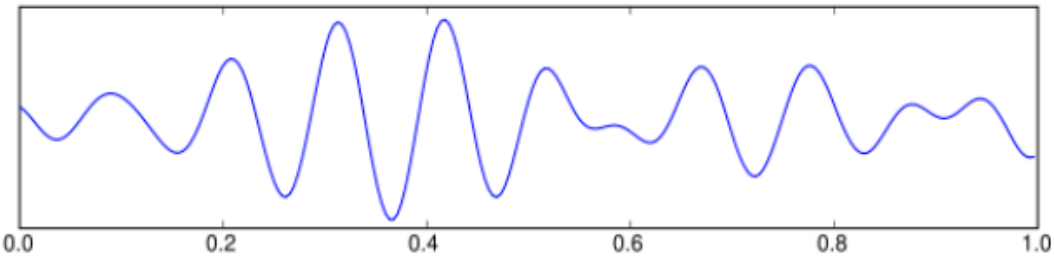
I.) Delta (∂) has a frequency of 4 Hz or below. It is normally seen in deep sleep [31]. Delta wave pattern looks like this:



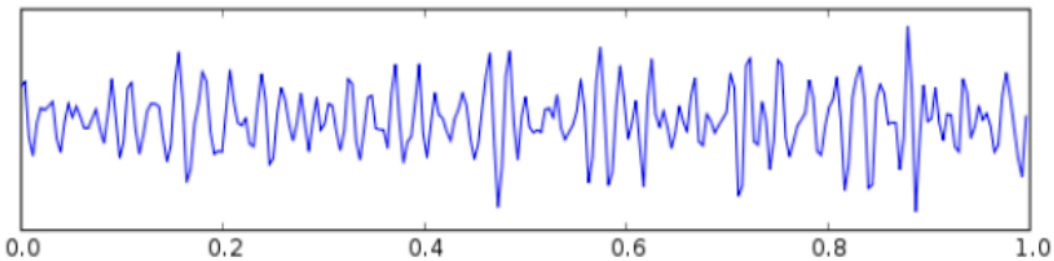
II.) Theta (θ) has a frequency range between 4-8 Hz. It is associated with daydreams, lucid dreaming and light sleep states [31]. Theta wave pattern looks like this:



III.) Alpha (∝) has a frequency range between 8 Hz- 12 Hz. It is associated with relaxation without attention and concentration. [31]. Alpha wave pattern looks like this:



IV.) Beta (β) has the frequency range between 12 and 30 Hz. It is presented in the excited sate of mind when person is awake and with full mental activity [31]. Beta wave pattern looks like this:



2.2.3 Artifacts

Artifacts are undesired signals that are detected by an EEG but not belong to a cerebral origin. They may occur at many points during the recording process. It can be in two types; Physiologic, arising from body sites other than brain (i.e. eye blinking, heart beating, muscles etc.) and extraphysilogic, generated outside of the body (i.e. loose/broken electrode) [32].

I.) Power line artifact (extraphysilogic)

The most significant noise acquired is from the surrounding electromagnetic signals. This noise is very much higher than the interested signal, the typical value in the EEG without artifacts is from 10 to 100 microvolts where power line is from 10 millivolts to 1 volt [31]. Their signals are greater than 50 Hz [32].

II.) Muscle artifact (EMG)

Muscle artifacts are characterized by surges in high frequency activity and are readily identified because of their outlying high values relative to the local background activity [31]. Their frequencies are greater than 30 Hz.

III.) Eye blinks (EOG)

Blink artifacts are attributed to alterations in conductance arising from contact of the eyelid with the cornea [33]. Its frequency is lesser than 4 Hz.

IV.) Sweat artifact

Sweat contains water, minerals, lactate and urea. It can react with the electrodes altering their impedance and producing an unstable baseline. Over an extensive area of the scalp may result in a saline bridge and gives rise to low amplitude tracings (short circuiting) [34].

3. State of the Art

The study of emotions in human-computer interaction has been increased in recent years. Many methods for estimating human emotion have been proposed in the past. The conventional methods basically utilize audio and visual attributes to model human emotional responses, such as speech, facial expressions, and body gestures. However, emotions are not always manifested by means of facial expressions and voice information. Facial and voice information is related only to behavioral expression which can be consciously controlled and modified, and which interpretation is often subjective. Thus, other approaches to detect emotion have been proposed which focus on different physiological information such as heart rate, skin conductance, pupil dilation [35,36]. As compared with audio and/or visual-based methods, the responses of biosignals tend to provide more detailed and complex information as an indicator for estimating emotional states [37]. In addition to periphery biosignals, signals captured from the brain in central nervous system (CNS) have been proved to provide informative characteristics in responses to the emotional states. The ongoing brain activity recorded using EEG provides noninvasive measurement with temporal resolution in milliseconds. There are two lines of parallel work involved on emotion detection with EEG: One is the pure electro physiological work to acquire data; the second is the interpretation and understanding of the records, the separation of the important from the unimportant and apply machine learning algorithms to classify emotions. There have been several approaches to EEG-based emotion detection, but there is still little consensus about definite conclusions. In table 1 overall evaluation of the reviewed papers can be seen.

In 2000 Choppin proposed to use EEG signals for classifying six emotions based on emotional valence and arousal [7]. He characterized positive emotions by a high frontal coherence in alpha, and high right parietal beta power. Higher arousal (excitation) is characterized by a higher beta power and coherence in the parietal lobe, plus lower alpha activity, while dominance (strength) of an emotion is characterized as an increase in the beta / alpha activity ratio in the frontal lobe, plus an increase in beta activity at the parietal lobe.

In 2003 Ishino and Hagiwara [38] proposed a system that estimated subjective feeling using neural networks to categorize emotional states based on EEG features. They reported an average accuracy range from 54.5% to 67.7% for each of four emotional states.

In 2004 Takahashi [36] used a headband of three dry electrodes to classify five emotions (joy, anger, sadness, fear, and relaxation) based on multiple bio-potential signals (EEG, pulse, and skin conductance). He trained classifiers using support vector machines (SVM) and reports the resulting classifying accuracy both using the whole set of bio-potential signals, and solely based on EEG signals. The experimental results showed that the recognition rate using a support vector machine (SVM) reached an accuracy of 41.7% for five emotions.

In 2006 Oude [39] described an approach to recognize emotion from EEG signals measured with the BraInquiry EEG PET device. She uses a limited number of electrodes and trains a linear classifier based on Fishers discriminant analysis. She considers audio, visual and audiovisual stimuli and trained classifiers for positive/negative, aroused/calm and audio/visual/audiovisual.

In 2007 Heraz et al. [40] established an agent to predict emotional states during learning. The best classification in the study was an accuracy of 82.27% for distinguishing eight emotional states, using k-nearest neighbors as a classifier and the amplitudes of four EEG components as features.

In 2009 Chanel et al. [41] reported an average accuracy of 63% by using EEG time-frequency information as features and SVM as a classifier to characterize EEG signals into three emotional states.

In 2009 also Zhang and Lee [42] proposed an emotion understanding system that classified users' status into two emotional states with the accuracy of 73.0% ± 0.33% during image viewing. The system employed asymmetrical characteristics at the frontal lobe as features and SVM as a classifier.

In 2010 Lin at al. [43] applied machine learning techniques to categorize EEG signals according to subject self-reported emotional states during music listening. They propose a framework for systematically seeking emotion specific EEG features and exploring the accuracy of the classifiers. In particular, they applied support vector machines to classify four emotional states: joy, anger, sadness, and pleasure.

In 2012 Ramirez and Zacharias [8] proposed a method for detecting emotion from EEG signals using the Emotiv EPOC device. In their research subjects listened selected sounds from IADS library of emotion-annotated sounds [44]. They used arousal-valance emotion plane like in figure 6**,** and selected 12 sound stimuli situated in the extremes on the plane: three positive/aroused, three positive/calm, three negative/calm, and three negative/aroused. They measured the EEG signal in four locations in the prefrontal cortex: AF3, AF4, F3, and they used beta/alpha ratio as an indicator of the arousal state**.** For determining the valance level they compared the activation level between the two cortical hemispheres. They applied two machine learning techniques in order to classify emotional state of mind; Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM). For the high-versus-low arousal, and the positive-versus-negative valence classifiers the average accuracies they obtained for SVM with radial basis function kernel classifier were 77.82%, and 80.11%, respectively.

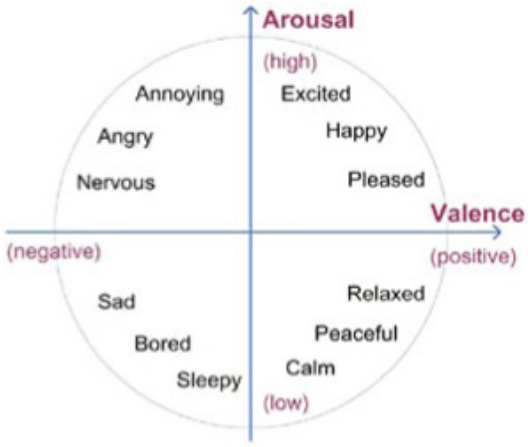


Figure 6. Emotional states and positions in the valance/arousal plane used by Ramirez and Zacharias (2012).

AUTHOR / YEAR	PREDICTION	CLASSIFIER	DEVICE (used electrodes)	STIMULE	ACCURACY
CHOPPIN / 2000	6 Emotions	Neural networks	EEG (13 Electrodes)	Pictures / Sound	64%
Takashi / 2004	5 Emotions	SVM	EEG (3 Electrodes), Pulse, Skin Conductance	Audio / Video	41.7%
OUDE /2006	Modality, Arousal and Valance Levels	FDA and VA-ARO	EEG PET(5 electrodes-frontal cortex)	IADS / IAPS	~80%
Harez et al. / 2007	8 Emotions	k-NN	Pendant EEG (3 electrodes)	IAPS	~80%
Lin et al. / 2010	4 Emotions	SVM	Neuroscan (32 channels)	Music Soundtrack	~82%
Liu Y. et al. / 2012	6 Emotions	Fractal Dimensions and VA-ARO	Emotiv EPOC (14 electrodes)	IADS / IAPS	-
Ramirez R. et al. / 2012	Arousal and Valance Levels	LDA and SVM	Emotiv EPOC(4 electrodes-frontal cortex)	IADS	77.82% 80.11%

Table 1. Overview of the recent studies has been done in emotion prediction using EEG.

4. Materials and Methods

4.1 Materials

4.1.1 Musical Data

Six songs with emotional content of happy, sad and relax were retrieved; Three of them (one for each emotional content) were chosen among the database of songs that were previously classified by emotional moods by signal processing, machine learning and information retrieval techniques [6]. Table 2 shows the songs that were selected for this dataset. This dataset is referred as common songs in this study due to they were listened by all of the participant subjects during the experiment. The other three songs (one for each emotional content) were selected by subjects particularly according to their preferences while subjects were encouraged to choose songs that will evoke desired emotions in the experiment. Table 3 shows the songs that were selected by subjects. This musical dataset is referred as subjects' selected songs in this study. The first two minutes of the each song was used during the experiment.

Common Songs	HAPPY	SAD	RELAX
	Ace of Base-Life Is a Flower/Flowers (1998)	Anathema-Are You There/A Natural Disaster (2003)	Zero 7-In the Waiting Line/Simple Things (2004)

Table 2. Shows the common songs that were listened by all participating subjects. Songs names appear as: Name of the artist-Name of the song/Title of the album (year)

Subjects' Selected Songs	HAPPY	SAD	RELAX
Subject 1	Daft Punk- One More Time/Discovery (2002)	Slipknot-Vermillion Part 2/Vol. 3: (The Subliminal Verses) (2004)	Ed Sheeran-I See Fire/Single (2013)
Subject 2	Soggy Bottom Boys-I Am a Man of Constant Sorrow/O Brother, Where Art Thou? (2000)	Trespassers William-Love Is Blindness/B-Sides (2011)	Edgar-Voyage/Voyage (2005)
Subject 3	Andy McKee-Rylynn/Art of Motion (2006)	Andy McKee-When She Cries/Dreamcatcher (2004)	Bonobo-Cirrus/The North Borders (2013)
Subject 4	Bob Marley & The Wailers-Is This Love/Kaya (1978)	Moby-Whispering Wind/Play (2000)	A-ha-Summer Moved On/Minor Earth | Minor Sky (2000)
Subject 5	Naxxos-New Orleans/ (2013)	Mumford & Sons-Liar/Mumford & Sons (2008)	The National-Slow Show/Boxer (2007)
Subject 6	Klingande-Jubel/Jubel EP (2013)	Gadsdens-The Sailor Song/Autoheart (2007)	Explosions In The Sky-Your Hand In Mine/The Earh Is Not a Cold Dead Place (2003)
Subject 7	Trentemoller, Marie Fisker-Candy Tongue/Lost (2013)	Dimmu Borgir-Avmakt Slave (?)	Bohren & Der Club of Gore-Constant Fear/Black Earth (2002)
Subject 8	Micheal Buble-Haven't Met You Yet/Crazy Love (2009)	Adele-Someone Like You/21 (2011)	Melody Gardot-If The Stars Were Mine/My One and Only Thrill (2008)
Subject 9	The Beatles-She Loves You/The Beatles' Second Album (1964)	Radiohead-You Never Wash Up After Yourself/The Bends (2009)	Maria Anamaterou-Den Ximeroneis/Opou Agapas Kai Oppu Gis (2011)
Subject 10	Banda Blanca-Sopa de Caracol/Single (1991)	Extrechinato y Tu-Abrazado a la Tristeza/Poesia Basica (2011)	Chicha Libre-Gnosienne No. 1/Sonido Amazonico (2008)
Subject 11	Dr. Dog - Shadow of people/Shame,Shame(2010)	Beatles-Hey jude minor scale	Gabriel Faure-Requiem(1887)

Table 3. Shows the songs that were chosen by subjects. Songs names appear as: Name of the artist-Name of the song/Title of the album (year).

4.1.2 Emotiv EPOC

Electrical activity of the brain was captured by Emotiv EPOC neuroheadset [45], which has 14 electrodes, plus 2 electrodes for reference and noise reduction. The electrodes are located and labeled according to aforementioned 10-20 electrode placement system (section 2.2.1) [27]. The available electrode positions can be seen in figure 7.

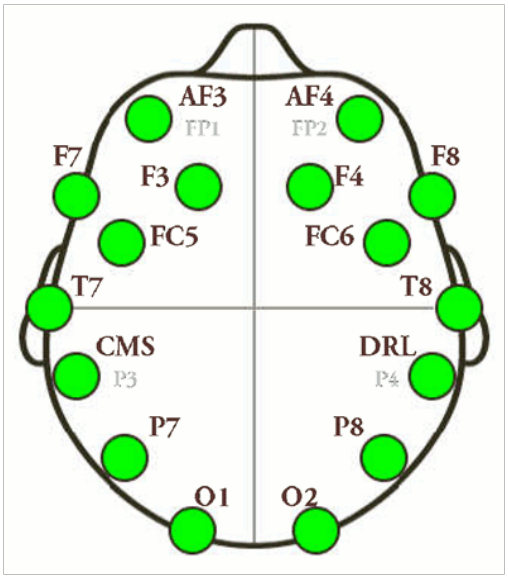


Figure 7. Available electrode positions on Emotiv EPOC according to 10-20 electrode placement system.

4.1.3 OpenViBE

OpenViBE is an open-source graphical programming language that is mainly designed for brain-computer interface (BCI) applications. It lets user to work with over 15 EEG acquisition devices, Emotiv EPOC is one of them [46].

In this study OpenViBE was used to retrieve EEG signals from Emotiv EPOC neuroheadset. And furthermore OpenViBE was used to process the acquired EEG signals in order to retrieve necessary EEG features.

4.1.4 Weka

Weka is an open-source data mining software, which has a collection of machine learning algorithms and tools for data pre-processing, classification, regression, clustering, association rules, and visualization [47].

Weka was used to classify EEG data in this study.

4.1.5 MIRtoolbox

MIRtoolbox offers a set of functions written and to be used in Matlab, dedicated to extraction of musical features from audio files [48].

In this study musical data was processed with MIRtoolbox and necessary musical features were retrieved.

4.1.6 MATLAB

MATLAB is an interactive environment for numerical computation, visualization and programming [49].

In this study MATLAB was used to investigate the correlations between the EEG features that were retrieved by OpenViBE with the musical features that were retrieved by MIRtoolbox.

4.2 Methods

Methods are presented in two sections. In section 4.2.1 experiment setup is presented, this section gives information about how the EEG data is retrieved. In section 4.2.2 data analysis is described, this section gives information about how the musical and EEG data are analyzed.

4.2.1 Experiment

Experiment was designed in order to retrieve proper EEG data while subjects were listening to music from aforementioned musical datasets (refer to table 2 and table 4). Eleven subjects, aged between 24-29, participated to the experiment. Nine of the participated subjects were males and two was female.

Before the experiment informed consent was presented to the subjects and experiment was explained. The subjects were informed to sit in a confortable position, keep their eyes closed and not to move during the experiment. Emotiv EPOC device was posed on the scalp of the subjects and guaranteed that all of the electrodes were working properly.

Subjects were presented to listen six music excerpts as the first two minutes of the selected songs were presented. Firstly, three excerpts from common songs dataset were presented in the order of happy, sad and relax. Timeline of this presentation can be seen in table 4. Secondly, three excerpts from the songs they had chosen were presented in the order of happy, sad and relax. Timeline of this presentation can be seen in table 5. While subjects were listening first two minutes of the songs in the mentioned order, 15 seconds of silence was given after each song. During these breaks subjects were asked to rate their emotional state relevant to in which emotional content of music they were previously listened to. They rated their emotional state between 1 and 5. A score of 5 denotes that subject intensively felt the relevant emotional state during the listening while a score of 1 denotes he/she didn't feel the related emotion at all. This self-assessed emotion rating was done with oral feedback.

Time (s) / Category	0-15	16-135	136-150	151-270	271-285	286-405
Silence	X		X		X	
Happy		X				
Sad				X		
Relax						X

Table 4. Timeline of the experiment for the common songs. Table shows time intervals in seconds and when the songs and silences were appeared during the experiment.

Time (s) / Category	406-420	421-540	541-565	566-685	686-700	701-820
Silence	X		X		X	
Happy		X				
Sad				X		
Relax						X

Table 5. Timeline of the experiment for the songs acquired from subjects. Table shows time intervals in seconds and when the songs and silences were appeared during the experiment.

4.2.2 Data Analyses

The data analyses are presented in two sections. Section 4.2.2.1 presents how the EEG data was analyzed in order to classify it with the relevant emotional category. Section 4.2.2.2 presents how the audio was analyzed in order to find correlations between EEG data.

4.2.2.1 EEG Analysis

The raw EEG data, acquired from OpenViBE software during the experiment, was analyzed in order to provide necessary EEG features for classification and correlation purposes. EEG signals were acquired from all available 14 electrodes of Emotive EPOC neuroheadset; AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1, O2.

Two different time epochs were applied to the retrieved raw EEG data. Firstly 1 second of window length and 0.1 second of hop-size were applied in order to be used for EEG classification. Secondly 1 second of window length and 1 second of hop-size were applied in order to be used for musical features and EEG features correlations. This second time epoch was determined due to high computational power needs for musical feature extraction.

For each electrode their θ (theta), ∝ (alpha) and β (beta) bands were calculated by applying band pass filter as following parameters, respectively: 4-8 kHz, 8-12 kHz, 12-30 kHz.

High-level EEG features (arousal and valence variations) were calculated. Extracted high-level features and how they were calculated can be seen it the table 6 and table 7.

Totally 83 EEG features were extracted; θ, ∝, β bands for each electrode, high-level EEG features and the raw EEG signals as their selves.

EEG Features	Description	Formula
VALENCE AF	Valence value between AF4 and AF3 electrodes	$(\beta AF_4 / \propto AF_4) - (\beta AF_3 / \propto AF_3)$
VALENCE FRONTAL	Valence value between AF4, F4 and AF3, F3 electrodes	$[(\beta AF_4+\beta F_4) / (\propto AF_4+\propto AF_4)] - [(\beta AF_3+\beta F_3) / (\propto AF_3+\propto F_3)]$
VALENCE ALL	Valence value between all right hemisphere (AF4, F4, F8…) and left hemisphere (AF3, F3, F7…) electrodes	$[(\beta AF_4+\beta F_4 \ldots+\beta O_2) / (\propto AF_4+\propto AF_4 \ldots+\beta O_2)] - [(\beta AF_3+\beta F_3 \ldots+\propto O_1) / (\propto AF_3+\propto F_3 \ldots+\propto O_1)]$
VALENCE RAW AF4	Valence value between raw AF4 and AF3 signal	$AF_4 - AF_3$
VALENCE RAW F4	Valence value between raw F4 and F3 signal	$F_4 - F_3$
VALENCE RAW F8	Valence value between raw F8 and F7 signal	$F_8 - F_7$
VALENCE RAW FC6	Valence value between raw FC6 and FC5 signal	$FC_6 - FC_5$
VALENCE RAW T8	Valence value between raw T8 and T7 signal	$T_8 - T_7$
VALENCE RAW P8	Valence value between raw P8 and P7 signal	$P_8 - P_7$
VALENCE RAW O2	Valence value between raw O2 and O1 signal	$O_2 - O_1$
AROUSAL AF	Arousal value for AF electrodes	$(\beta AF_4 + \beta AF_3) / (\propto AF_4 + \propto AF_3)$
AROUSAL FRONTAL	Arousal value for AF and F electrodes	$(\beta AF_4 + \beta AF_3 + \beta F_4 + \beta F_3) / (\propto AF_4 + \propto AF_3 + \propto F_4 + \propto F_3)$
AROUSAL ALL	Arousal value for all available 14 electrodes	$(\beta AF_4 + \beta AF_3 \ldots + \beta O_2 + \beta O_1) / (\propto AF_4 + \propto AF_3 \ldots + \propto O_2 + \propto O_1)$

Table 6. High-level EEG features, their descriptions and the formulas that were used to calculate them. Features continues in table 7

EEG Features	Description	Formula
AROUSAL AF3	Arousal value for AF3 electrode	$\beta AF_3 / \propto AF_3$
AROUSAL AF4	Arousal value for AF4 electrode	$\beta AF_4 / \propto AF_4$
AROUSAL F3	Arousal value for F3 electrode	$\beta F_3 / \propto F_3$
AROUSAL F4	Arousal value for F4 electrode	$\beta F_4 / \propto F_4$
AROUSAL F7	Arousal value for F7 electrode	$\beta F_7 / \propto F_7$
AROUSAL F8	Arousal value for F8 electrode	$\beta F_8 / \propto F_8$
AROUSAL FC5	Arousal value for FC5 electrode	$\beta FC_5 / \propto FC_5$
AROUSAL FC6	Arousal value for FC6 electrode	$\beta FC_6 / \propto FC_6$
AROUSAL T7	Arousal value for T7 electrode	$\beta T_7 / \propto T_7$
AROUSAL T8	Arousal value for T8 electrode	$\beta T_8 / \propto T_8$
AROUSAL P7	Arousal value for P7 electrode	$\beta P_7 / \propto P_7$
AROUSAL P8	Arousal value for P8 electrode	$\beta P_8 / \propto P_8$
AROUSAL O1	Arousal value for O1 electrode	$\beta O_1 / \propto O_1$
AROUSAL O2	Arousal value for O2 electrode	$\beta O_2 / \propto O_2$

Table 7. High-level EEG features, their descriptions and the formulas that were used to calculate them. Continuation of table 6

In order to predict music category the subjects were listening to, data classification methods were applied using the Weka program. The extracted high-level EEG features were input to Weka and four different classification methods were applied using 10-fold cross validation; Support Vector Machines (SVM) [50], Decision Tree, Multilayer Perceptron (MLP) [51] and kth Nearest Neighbor (k-NN) [52].

In order to detect emotional state of the subjects the mean values of high-level EEG features were calculated. Subjects that were satisfying accepted arousal and valence constraints were plotted. For a subject, valence constraint is fulfilled if the happy and relax valence averages are greater than the average for sad. The arousal constraint is fulfilled if the happy arousal average is greater than the arousal average for both sad and relax.

4.2.2.2 Audio Analysis

Audio analysis covers the process of musical feature extraction. Musical features were extracted using MIRtoolbox in MATLAB environment. 43 musical features were retrieved; 20 of them were belonging to timbre, 3 of them to dynamics, 4 of them to pitch, 8 of them to rhythm and 8 of them to tonality properties of the music. Frame based extraction were applied using 1 second of window length and 1 second of hop-size and also standard deviations for the necessary musical features that had array of results were calculated. Extracted musical features, their description and their category is given in the table 8 and table 9. The extracted musical audio datasets are mentioned in table 2 and table 3.

Musical Features	Description	Musical Category
Attack Time	Time between the start of the signal and when it reaches its peak	Timbre
Attack Slope	Average slope of the attack time	Timbre
STD (Attack Slope)	Standard deviation of the attack slope	Timbre
Roughness Mean	Mean of the estimation of the sensory dissonance, frequency ratio of each pair of sinusoids [53]	Timbre
Brightness Mean	Mean of the amount of energy above cut-off frequency	Timbre
STD (Brightness)	Standard deviation of the brightness	Timbre
Spectral Centroid Mean	Mean of the barycenter of the spectrum	Timbre
STD (Spectral Centroid)	Standard deviation of the spectral centroid	Timbre
Zero-Crossing Rate Mean	Mean of the number of time the signal value cross zero axe.	Timbre
STD (Zero-crossing Rate)	Standard deviation of the zero-crossing rate	Timbre
Spectral Spread	The variance of the spectral centroid	Timbre
Spectral Skewness	Asymmetry of the spectrum around its mean value.	Timbre
Entropy Mean	Mean of the Shannon entropy of the signal	Timbre
STD (Entropy)	Standard deviation of the entropy	Timbre
Spectral Flux Mean	Mean of the distance between the spectrum of each successive frames	Timbre
Flatness	Value of the noisiness / sinusoidality of a spectrum	Timbre
Regularity Mean	Mean of the irregularity of a spectrum	Timbre
STD (Regularity)	Standard deviation of the regularity	Timbre
MFCC Mean	Mel Frequency Cepstral Coefficients is shape of the spectrum with coefficients. (The coefficients of the MFCC appear in parenthesis, i.e. MFCC(1),…)	Timbre
MFCC Delta Mean	Mean of the first order if the MFCC along time	Timbre
Rms	Root-Mean Square Energy. It is the root average of the square of the amplitude [48]	Dynamics
STD (Rms)	Standard deviation of the calculated rms.	Dynamics
Low Energy	The percentage of frames showing less-than-average energy [53]	Dynamics

Table 8. Musical features that were extracted by MIRtoolbox, their descriptions and their categories. Continues at table 9

Musical Features	Description	Musical Category
Pitch Mean	Mean of the pitch value	Pitch
STD (Pitch)	Standard deviation of the pitch	Pitch
Inharmonicity Mean	Mean of the amount of partials that are not multiples of the fundamental frequency. Returns values between 0 and 1	Pitch
STD (inharmonicity)	Standard deviation of the inharmonicity	Pitch
Fluctuation	Rhythmic periodicity along auditory channels [48]	Rhythm
Fluctuation Centroid	Centroid of the fluctuation	Rhythm
Fluctuation Peak Position Mean	Mean of the positions of the fluctuation peaks appeared	Rhythm
Fluctuation Peak Value Mean	Mean of the fluctuation peak values	Rhythm
Tempo Mean	Mean of the Periodicities detected from the onset detection curve [48]	Rhythm
STD (Tempo)	Standard deviation of the tempo	Rhythm
Pulse Clarity Mean	Mean of the Rhythmic clarity [54]	Rhythm
STD (Pulse Clarity)	Standard deviation of the pulse clarity	Rhythm
Chromagram Mean	Mean of the energy distribution along pitches	Tonality
STD (Chromagram)	Standard deviation of the chromagram	Tonality
Chromagram Entropy	Entropy of the chromagram	Tonality
Key Strength Mean	Mean of the key strength along each possible key candidate. Returns values between -1 and +1	Tonality
STD (Key Strength)	Standard deviation of the key strength	Tonality
Mode Mean	Mean of the modality. Returns values between -1 and +1 as close to the minor or major modes, respectively	Tonality
STD (Mode)	Standard deviation of the mode	Tonality
HCDF	Harmonic Change Detection Function is the flux of the tonal centroid [55]	Tonality

Table 9. Musical features that were calculated by MIRtoolbox, their descriptions and their categories. Continuation of table 8

5. Results And Discussion

The results are presented in three sections. In section 5.1, subjects' self-assessment of their emotional response to listening to different music pieces is presented. In section 5.2 the results of EEG data classification are presented, and finally, in section 5.3 the correlations between musical features and EEG features are reported. These results are discussed at the end of the chapter.

5.1 Emotional State Feedback Results

The average of the subjects' self-assessed emotional state scores is shown in table 10. The scores range between 1 and 5. A score of 5 denotes that a subject intensively felt the relevant emotional state during music listening while a score of 1 denotes he/she didn't feel the related emotion at all. The common happy song was proved to be the least emotion-evoking song as the average score for it is 2.6 out of 5. The common sad song has an average score of 3.3 while the common relax song has an average score of 4.1 out of 5. At the same time, subject chosen songs produced more intense emotions (subject-happy, subject-sad and subject-relax songs averages score of 4.6, 4,4 and 4.6, respectively).

Common Happy	Common Sad	Common Relax	Subject Happy	Subject Sad	Subject Relax
2.6	3.3	4.1	4.6	4.3	4.6

Table 10. The average rates of feedbacked emotional state that music's evoked while subjects were listening to relevant songs.

5.2 EEG Classification Results

EEG data obtained from 6 different music categories (happy, sad, relax categories for common and subject selected songs) was used to train classifiers with Support Vector Machines (SVM), decision tree, Multilayer Perceptron (MLP) and k Nearest Neighbor (k-NN) classification algorithms to predict the music category. Only high-level EEG features (table 6 and table 7) were used to train the classifiers. The reported results were obtained using 10-fold cross validation.

The obtained accuracy results, for each subject and for each classification method, are shown in table 11. K-NN and decision tree algorithms obtained the best accuracies with averages of 98.2% and 88.9%, respectively. Average accuracies of Multilayer Perceptron (MLP) and SVM are 75.8% and 53.5%, respectively while the base-line accuracy is 16.6.

Subject #	SVM %	Decision Tree %	MLP %	k-NN %
Subject 1	78.9	93.7	84	99.3
Subject 2	50.5	90.3	71	98.7
Subject 3	45.9	89.7	71.4	98.7
Subject 4	34.2	79.3	81.9	99.1
Subject 5	60.6	90.6	80.7	99.1
Subject 6	75	92.7	85.3	99.5
Subject 7	45.21	81	62.7	97.2
Subject 8	38.7	85.4	68.9	94.6
Subject 9	40.1	92.7	72.5	96.7
Subject 10	55.4	91.7	75.5	98
Subject 11	64	90.4	80.1	99.3
Average	53.5	88.9	75.8	98.2

Table 11. Classification results of 6 musical category with high-level EEG attributes using classifiers: SVM, Decision Tree, MLP, and k-NN with 10 folds cross-validation while the base-line classification accuracy is 16.6

For illustration purposes, the confusion matrix showing the classification accuracies results of the multilayer perceptron classifier for subject 10 is shown in table 12. Due to overall tendency of confusion matrixes stayed similar for each subject and for each classification method the rest of the matrixes were not included here. For each category there were 1270 instances. As the confusion matrix shows the correctly predicted instances were above 907 for each category for subject 10 with MLP classifier. For instance, 1207 instances of happy common EEG features were predicted correctly and the rest 63 instances were mispredicted as sad common.

Predicted Category / Real Category	Happy Common	Sad Common	Relax Common	Happy Subject	Sad Subject	Relax Subject
Happy Common	1207	63	0	0	0	0
Sad Common	54	1108	53	11	42	2
Relax Common	32	36	1011	74	69	48
Happy Subject	0	5	45	945	111	164
Sad Subject	0	18	95	155	907	95
Relax Subject	0	7	26	244	68	925

Table 12. Confusion matrix of the subject 10. Multilayer perceptron used as a classifier with 10-fold cross validation

The mean value of each high-level EEG feature for each category was calculated in order to plot how many subject satisfied the valence and arousal constraints as appears in figure 6. For a subject, the valence constraint is fulfilled if the happy and relax valence averages are greater than the average of the valence for sad. The arousal constraint is fulfilled if the happy arousal average is greater than the arousal average for both sad and relax. These constraints represent the expected patterns among arousal and valence values for the three categories. In table 13, the high-level EEG features that satisfied these constraints for at least 5 subjects in one category are shown. In addition, the important arousal and valence features are shown in the table, as they were found relevant for mode estimation in previous studies [26,8]. The important arousal and valence features included in the table even they weren't satisfied by 5 subjects are Arousal AF, Arousal Frontal, Arousal All, Valence AF and Valence All.

Category	**AROUSAL AF**	**AROUSAL FRONTAL**	**AROUSAL ALL**	**AROUSAL AF3**	**AROUSAL FC5**	**AROUSAL FC6**	**AROUSAL O1**	**AROUSAL T7**	**AROUSAL F7**
Common Songs	4	4	4	5	7	6	3	5	5
Subject Selected Songs	2	3	4	1	3	5	6	5	0
Category	**VALENCE AF**	**VALENCE FRONTAL**	**VALENCE ALL**	**VALENCE RAW F4**	**VALENCE RAW T8**	**VALENCE Raw P8**	**AROUSAL P7**	**AROUSAL F8**	
Common Songs	3	6	4	5	5	5	5	5	
Subject Selected Songs	3	4	4	2	3	2	4	4	

Table 13. Number of subjects that satisfies arousal and valence constrains. High-level EEG feature mean values that satisfied the arousal and valence constraints. The high-level EEG features were chosen among EEG features that were found relevant in previous studies [26,8] and from the features that had at least 5 subjects in one of the category

5.3 Musical Features and EEG Features Correlations

Musical features and EEG features correlations results are shown in three sections. Firstly, correlations for the subjects' selected songs will be shown, secondly correlations of the common songs will be shown, and finally a common EEG feature found coherent for common and subjects' selected songs will be shown. The musical features used to obtain these results were mentioned in the previous chapter. All of the calculated EEG features are included in these results; used EEG features were θ, $\propto$ and β bands of each of the 14 electrodes, raw signals of the electrodes and high-level EEG features as mentioned in table 6 and table 7. The EEG data used in these results was obtained by using 1 seconds of window size and 1 seconds of hop-size, as it was the case for calculating the features of the musical data.

In order to obtain the most correlated features some thresholds were chosen. The correlation dataset that is used in the following sections was chosen among the correlations that had correlation coefficient values greater than 0.1 and p-values lower than 0.05.

5.3.1 Subjects' Selected Songs

Correlations that have more than 0.25 correlation coefficient, with p-values of less than 0.05 and which were present in at least 7 subjects are shown in figure 8. In total, there were 10 different music-EEG feature pairs, which were satisfied these constraints. Among all 10 pairs, β-T7 EEG feature was found correlated with different musical features. Rms slope and STD (Rms) musical features provided the best correlation coefficient value as 0.325 and 0.317, and with a p-value of 0.006 and 0.0001, respectively (7 subjects fulfilled the required constraints). Entropy and β-T7 music-EEG feature pair was found correlated in 9 subjects with a correlation coefficient value of 0.28 and with a p-value of 0.001. MFCC (1), Rms, Spectral Centroid, MFCC (2) and zero-crossing rate were found correlated in 8 subject with correlation coefficient values of 0.292, 0.287, 0.266, 0.263, 0.252 and with p-values of 0.002, 0.008, 0.0009, 0.003, 0.001, respectively. Spectral Flux and MFFC(3) features were founded correlated in 7 subjects with correlation coefficient values of 0.273 and 0.253, and with p-values of 0.001, 0.003, respectively.

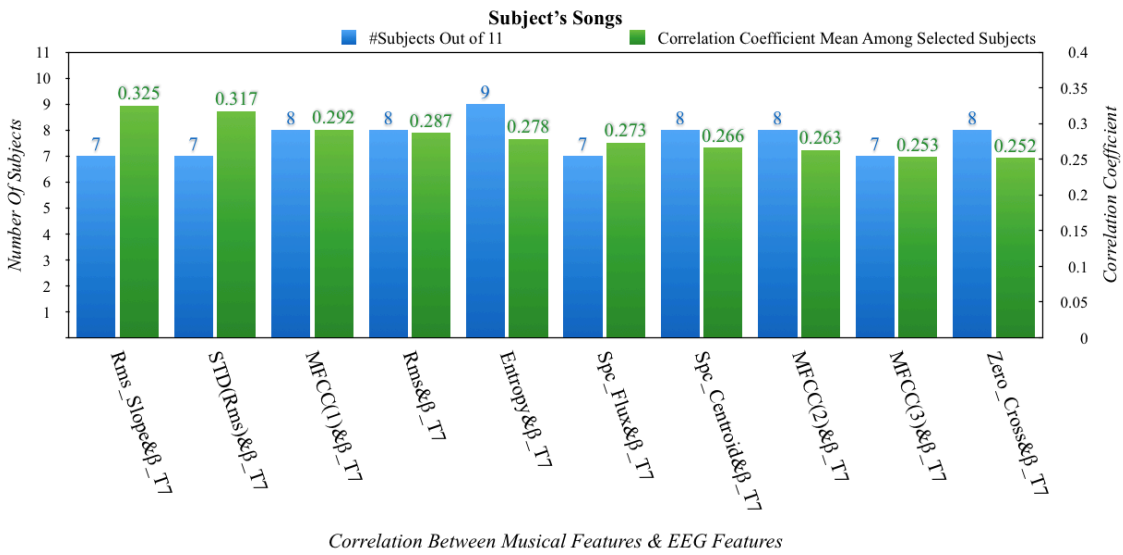


Figure 8. Correlation pairs between subject's selected song's musical features and their related EEG features. The plotted features were selected among correlations that had more then 0.25 correlation coefficient value, had less then 0.05 P value and that were satisfied by at least 7 subject

5.3.2 Common Songs

The correlations between the musical features of the songs that were presented to all of the subjects and their EEG data is shown in figure 9 and figure 10. The same constraints were applied to plot correlations with the subject's selected songs; The plotted features were selected among correlations that had more then 0.25 correlation coefficient value, had less then 0.05 p-value and that were satisfied by at least 7 subjects.

There were a total of 26 correlations that satisfied the constraints. The highest correlations were seen between Flatness & Valence Raw F8, Entropy & Valence Raw FC6, MFCC(1) & β-T7, Spectral Centroid & Valence Raw FC6 with the correlation coefficient values of 0.323, 0.321, 0.315, 0.314 in 7,8,7,8 subjects, respectively and with P-values below 0.01.

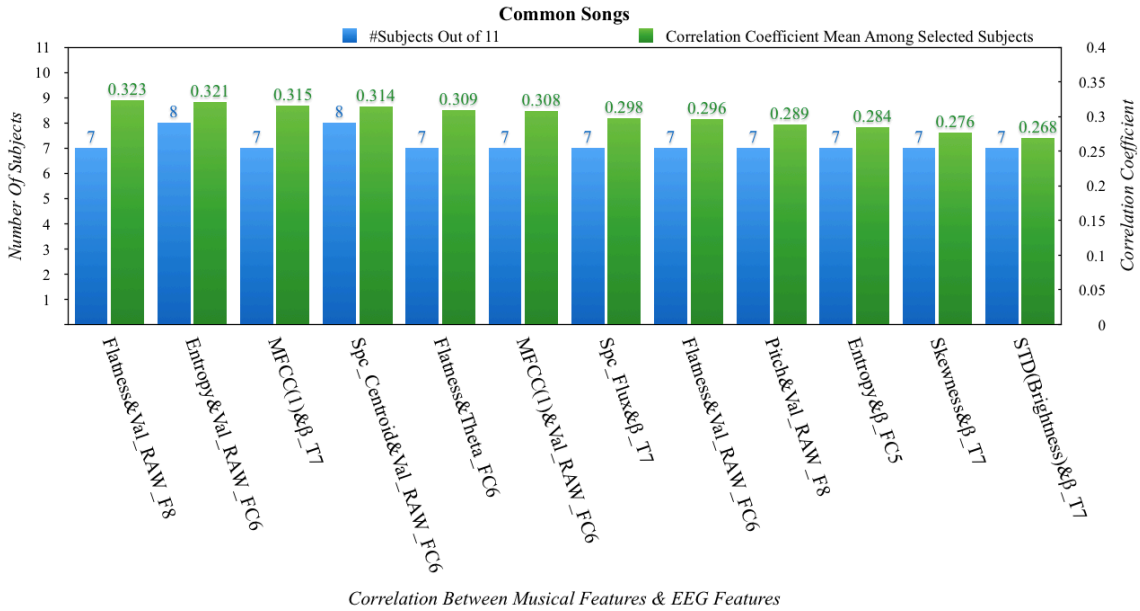


Figure 9. Correlation pairs for common songs' musical features and the EEG features. The plotted features were selected among correlations that had more then 0.25 correlation coefficient value and that had more than 6 subjects. The figure continues at figure 10.

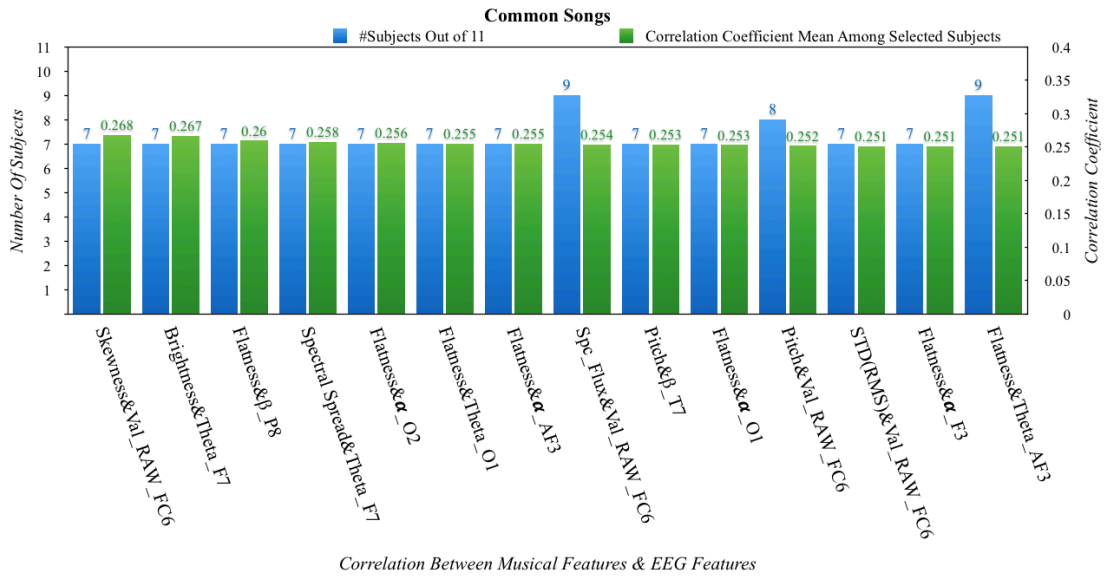


Figure 10. Continuation of figure 9. Shows correlations that had more than 0.25 correlation coefficient and had more than 6 subjects.

Even though there were 26 correlations the obtained p-values were not as low as the ones obtained in subjects' selected songs. In order to provide better p-values another constraints were determined; by lowering the subject limit to 6 and raising the correlation coefficient limit to 0.3. New pairs that were satisfying this constraint is shown in figure 11. In this case, Entropy & β-T7, Spectral Centroid & β-T7, Flatness & Valence Raw F4, Flatness & ∝ FC6, MFCC (3) & Valence Raw FC6 showed higher correlation coefficient values and lower p-values (<0.005). The correlation coefficient values were 0.372, 0.369, 0.351, 0.336, and 0.324, respectively while each correlation satisfied by 6 subjects.

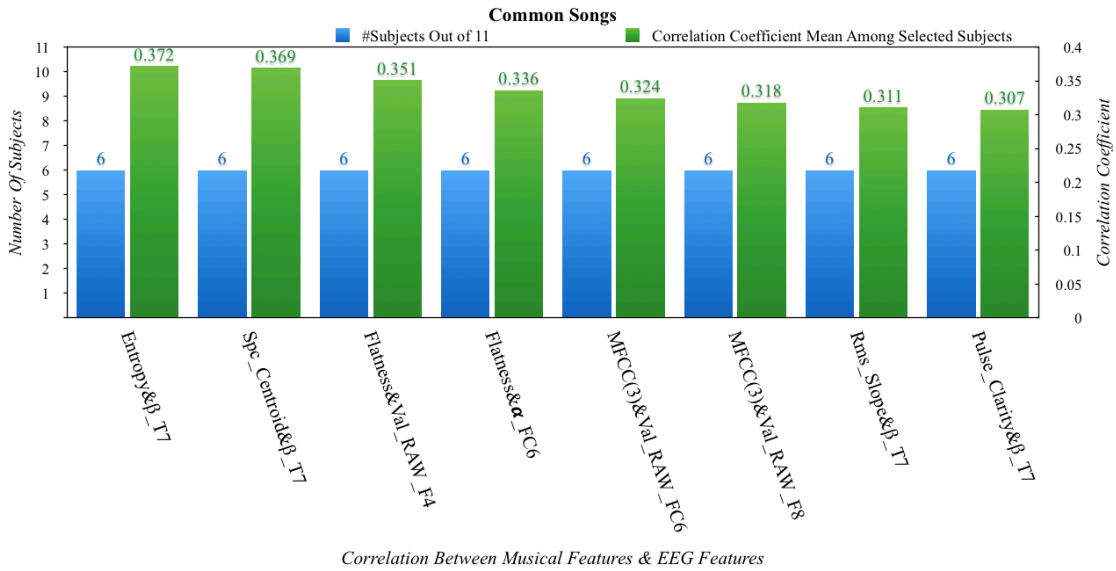


Figure 11. As an addition to figure 9 and figure 10 correlation pairs that had more than 0.3 correlation coefficient value and that had at least 6 subjects.

5.3.3 Mutual EEG Feature Correlated With Subjects' Selected Songs and Common Songs Musical Features

The β T7 EEG feature appeared in all of the correlations that satisfied the determined constraints for the subjects' selected songs musical features and EEG features correlation. And it appeared 5 times in the common songs musical features and EEG features correlation for the first constraint among 26 correlations and for the second constraint determined it appeared 4 times among 8 correlations. Table 14 shows the mutual β T7 EEG features and musical features that had more than 0.25 correlation coefficient, had less than 0.05 p-value and at least satisfied by 6 subject or if the correlation was satisfied more than 6 subjects. Entropy, MFCC (1), MFCC (3), RMS Slope, RMS, Spectral Centroid, Spectral Flux and Zero-crossing Rate were the musical features that satisfied those constrains with the p-values below 0.008.

Correlation	#Subjects Out of 11	Correlation Coefficient Mean	P Value Mean
Entropy&β_T7	9	0.278161	0.003102
Entropy&β_T7	6	0.371804	0.000071
MFCC(1)&β_T7	8	0.291541	0.002659
MFCC(1)&β_T7	7	0.315388	0.009845
MFCC(3)&β_T7	7	0.253211	0.003368
MFCC(3)&β_T7	8	0.249528	0.004211
Rms_Slope&β_T7	7	0.324841	0.006283
Rms_Slope&β_T7	6	0.310533	0.003302
Rms&β_T7	8	0.286898	0.008007
Rms&β_T7	6	0.261657	0.006183
Spc_Centroid&β_T7	8	0.265806	0.000909
Spc_Centroid&β_T7	6	0.369254	0.003205
Spc_Flux&β_T7	7	0.273208	0.001889
Spc_Flux&β_T7	7	0.297838	0.007446
Zero_Cross&β_T7	8	0.252043	0.001439
Zero_Cross&β_T7	7	0.224081	0.008915

Table 14. Shows the mutual β_T7 EEG feature correlation with subject chosen song features and common song features. The black written correlations represent subjects' chosen songs and blue written correlation represents common songs. Correlations were chosen if their correlation coefficient value was above 0.25, P value was below 0.05 and at least satisfied by 6 subjects or if the correlation was satisfied at least by 7 subjects.

5.4 Discussion

Discussion is divided in to two parts. In the first part EEG classification results will be discussed and in the second part musical and EEG features correlations results will be discussed.

5.4.1 EEG Classification Results Discussion

Obtained classification accuracies for the 6 categories were high; using k-NN classification method a 98.2% of mean accuracy was obtained. Although each category was predicted well with using different classifier methods, categories that share same emotional music type did not show any relation. The expected result was common songs and subjects' selected songs would evoke similar emotional states (for instance happy common song and happy subject selected song will evoke same emotional states) and classification results between them would show some commonality. In fact time might had been played a role in the classification. In the confusion matrix presented in table 12, correctly predicted and mispredicted classes could be seen. There was a time dependent tendency on mispredicted instances. As time interval gets wider between classes the mispredicted instances get lower. The expected results were as mentioned before to see more mispredicted instances along the classes that share same emotional content of music.

Also subjects' arousal and valence values could not presented a proof that listened music was evoking a relevant emotion. The number of subjects that satisfied the expected arousal and valence properties is given in table 13. Less then half of the subjects provide the expected arousal and valence properties.

5.4.2 Musical and EEG Features Correlation Discussion

The subjects' selected songs' musical features showed the highest correlations only with β T7 EEG feature along 10 distinct correlation with an average of p-value smaller than 0.004 and with an average correlation coefficient greater than 0.28. Musical features that were correlated with β T7 EEG feature were MFCC (1), Entropy, Spectral Flux, Spectral Centroid, MFCC (2), MFCC (3) and Zero-crossing Rate which were belonging to timbral properties of the music while Rms Slope, STD (Rms), Rms were related with dynamic properties of the music.

Common songs, with the same constraints applied to the subjects' selected songs, showed more correlations. There were 26 correlations that satisfied the constraints, 22 of them belonging the timbral, 3 of them belonging to pitch, and 1 of them belonging to dynamics properties of music. Unlike the subjects' selected songs, 5 of the correlations were belonging to β T7 EEG feature. And with the 8 correlations Valence Raw FC6 was the most appeared EEG feature among correlations. The reason why common songs showed more correlation than subjects' selected songs could be because of subjects weren't expect to listen these songs, songs were surprise for them and/or even they might not heard the songs before. On the other hand subjects were ready to hear their choice of songs and they might not be evoked much as common songs. So the common music might have a better effect on state of the mind due to there were 2.6 times more correlations than the subjects' selected songs correlations.

The musical features of common and subjects' selected songs showed mutual correlations between β T7 EEG feature. From the musical features that were proved to be mutual, Entropy, MFCC (1), MFCC (3), Spectral Centroid, Spectral Flux, Zero Crossing rate belong to timbral characteristic of the music, and Rms and Rms Slope belong to dynamics characteristic of the music.

6. Conclusions

In this study, music and emotion was investigated using electroencephalography (EEG) and music information retrieval (MIR) techniques. An experiment was designed in order to obtain EEG data while subjects were listening to music in six categories with three emotional content (happy, sad and relax); Three of the songs were preselected by us, while the other three was selected by subjects according their preference. 11 subjects participated to the experiment. Firstly EEG data was analyzed in order to classify these 6 categories. Machine learning techniques were applied to train classifiers to predict the category based on the EEG data of the subjects. The used algorithms for this purpose were SVM, Decision Tree, MLP and k-NN. The EEG data was also analyzed, with various arousal and valence features, in order to show if the EEG features present the emotional states of the subjects. Secondly, music audio was analyzed in order to show if the EEG features and musical features were correlated along time.

We manage to classify our 6 different categories with high accuracy. The achieved average accuracies were 55% for SVM, 88% for Decision Tree, 75% for MLP and 98% for k-NN. But we couldn't find relations between the categories with the same emotional content. Arousal and valence values alone were not able to satisfactorily describe categories with same emotional content whereas subjects' self reported emotional states indicate the contrary.

Some of the musical features were found to be correlated with EEG features. The most important EEG feature that was found to be correlated with musical features was β T7. The most correlated musical features with EEG features were timbral features while pitch, rhythm and tonality hadn't shown that much correlation with EEG features. β T7 showed correlation with 8 different musical features among both subjects' selected songs and common songs, with an average 0.29 correlation coefficient and 0.004 p-value.

7. Future Works

The role of window and hop-size wasn't investigated in this research. Musical and EEG features might be calculated with different window and hop-size and their effects on results might be investigated.

In the experiment the duration of one song excerpt was 120 seconds and maybe for the subject it was very hard to evoke the expected emotion during the entire song. The most emotionally relevant time interval of the EEG data could be marked and it could be used for EEG classification and even in musical and EEG features correlation calculations. This should be investigated further.

Feature selection methods could be applied to EEG data for classifying the type of the songs subjects were listening to. This could provide useful information for detecting which EEG features are the most relevant for discriminating the different categories.

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