EEG correlates of different emotional states elicited during watching music videos

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Abstract. Studying emotions has become increasingly popular in various research fields. Researchers across the globe have studied various tools to implicitly assess emotions and affective states of people. Human computer interface systems specifically can benefit from such implicit emotion evaluator module, which can help them determine their users' affective states and act accordingly. Brain electrical activity can be considered as an appropriate candidate for extracting emotion-related cues, but it is still in its infancy. In this paper, the results of analyzing the Electroencephalogram (EEG) for assessing emotions elicited during watching various pre-selected emotional music video clips have been reported. More precisely, in-depth results of both subject-dependent and subject-independent correlation analysis between time domain, and frequency domain features of EEG signal and subjects' self assessed emotions are produced and discussed.

Keywords: Emotion, electroencephalogram, power spectral density, normalized length density, non-stationarity index

1 Introduction

Although it is difficult to define, emotion can be considered as an overall psychophysiological process, influenced by many external and internal stimuli, such as personality, past experiences, affect and contextual environment to mention a few. Therefore, emotion is a continuous adaptive mechanism and serves the purpose of human interaction and expression, reaction to stimuli or events and re-evaluation of several circumstances. Since emotion is involved in every aspect of human life, it has gained a great deal of interest and attention in many research fields, such as neurology, psychology, sociology and computer science. In computer science, many researchers have endeavored to alter the "user-centered" orientation of human-computer interactions (HCI) systems and develop instead "human-centered" HCIs. This new term is more appropriate as it considers the overall human experience which is embodied in human emotions and interactions with machines. Nevertheless, current HCIs are still quite deficient in interpreting this affective information of emotion and they are still unable to take actions based on human emotion. Therefore, further insight has to be provided in this research area in order to equip machines with an affective functionality, which could make them more user-friendly, more sensitive to human beings and more efficient.

Until today, various theories for emotion modeling have been proposed, which mainly fall into categorical and dimensional modeling of emotions. The categorical models investigate and study different quasi-independent categories of emotions, and provide a list of basic emotions. These models are mainly represented by the basic six emotions proposed by Ekman and Friesen [1]. On the other hand, many dimensional theories for emotion modeling have been proposed, which investigate independent component and dimensions of emotion. Russell [2] describes emotions quantitatively using the valence-arousal space and argues that all emotions can be placed in this space. In other words, this is a two-dimensional model, with valence and arousal being the horizontal and the vertical axes, respectively. Although these two dimensions can describe most of the emotional variations, there is at times a third dimension of dominance included in the model [2]. Valence ranges from negative to positive (or unpleasant to pleasant), whereas arousal ranges from inactive (or calm) to active (or excited). Dominance ranges from weak (or without control) to an empowered and strong feeling (with control of everything).

Implicit assessment of emotion can be carried out through analysis of human expressions and physiological reactions. Human expressions comprise of verbal and non-verbal cues that can be processed using speech and face recognition systems. Physiological signals are also known to convey traces of emotion, but they have received less attention . Generally, physiological signals originate from the central nervous system (CNS) and the peripheral nervous system (PNS). Regarding the signals from the CNS, brain electrical activity has gained great interest for studying emotions. Thanks to the reasonable prices and the decent time resolution, EEG has become the main tool in brain research. Among other physiological signals, EEG has gained special interest because emotion is considered as a psychophysiological process which is directly reflected in brain activities.

Many scientists have tried to explore the correlations between different emotions and brain regions, but unfortunately, there is not much consistency among different studies [3]. For instance, according to Davidson's motivational model of emotion [4], left frontal brain activity indicates a positive emotion (high valence) whereas right frontal activity indicates a negative emotion (low valence). This is the phenomenon of "frontal EEG asymmetry", that has played a prominent role in affective EEG research. Moreover, Coan and Allen [5] have published a review of over 70 studies that examine the relationship between emotion and EEG frontal asymmetry. They argue that emotion correlates with EEG asymmetry are predominant and can be observed with different elicitation procedures. However, some studies, such as [6], failed to produce the similar expected results. On the other hand, several studies have reported that bilateral EEG activity can be also supported and mostly associated with negative emotions [7].

In the current study, we explore the EEG changes during different emotional states based on subjective and subject-independent analysis. Emotion elicitation is performed by watching music videos. In particular, subjective analysis is performed in order to estimate how different emotions contribute to brain region activation among different subjects. Subject-independent analysis is performed in order to investigate the common behavior of all subjects and draw general conclusions on how brain is affected by emotions while watching music videos. Emotion modeling is performed by using a three dimensional model of valence, arousal and liking (VAL). Liking dimension is added in order to capture the additional variations that cannot be identified by the other two dimensions. The analysis of the signals is performed both in time and in frequency domains. More specifically, for time domain we use two indexes that capture the complexity of the EEG time series, namely the normalized length density (NLD) [8] and the non-stationarity index (NSI) [9]. Furthermore, for the frequency domain we use the power spectral density (PSD) of the signals. Hence, the goal of the current study is twofold. First, to investigate how different EEG sub-bands and regions are affected by different emotional states, considering specific characteristics of the signals that are captured by features both in time and frequency domains. Second, to explore how these regions are affected in different subjects while they watch music video clips.

The paper is organized as follows. Section 2 describes the data and signal processing techniques used in this study. The results and further discussion are detailed in Section 3. Finally, the conclusions are presented in Section 4.

2 Materials and methods

2.1 Dataset

The experiments were performed in a laboratory environment with controlled temperature and illumination. EEG signals were recorded using a Biosemi ActiveTwo system through 32 active AgCl electrodes at sampling frequency of 512 Hz. Six participants were asked to view the 20 music videos, displayed in a random order. These music video clips were carefully selected using a subjective test. More information about the selection procedure can be found in [10]. Before displaying each video a 5-second long baseline was recorded. After each video was finished the participant was asked to perform a self-assessment of their levels of valence, arousal, and like/dislike which was later used as the ground truth.

2.2 PSD estimation

Before estimating the PSD of EEG signals, the data was re-referenced to the common average, down-sampled to 256 Hz and high-pass filtered with a cutoff frequency of 3 Hz using a Butterworth filter of third order. The eye-blinking artifacts were removed using RunICA algorithm implemented in EEGLAB toolbox[1]. Furthermore, in order to remove the influence of the stimulus-unrelated

[1] http://sccn.ucsd.edu/eeglab/

variations, a five second baseline was recorded before each trial. We processed the final one second of each baseline.

The frequency power of the signals and the baselines were extracted for frequencies between 4 and 47 Hz, using Welch's method with windows of 128 samples. The logarithm of the mean baseline power was then subtracted from the logarithm of the mean trial power, in order to extract the power changes without considering the pre-stimulus period. These power changes were captured for different brain bands, namely theta band (4-7 Hz), alpha band (8-13 Hz), beta band (14-29 Hz) and gamma band (30-47 Hz).

2.3 Complexity

Living organisms consist of complex structures and functions. In particular, parameters of the physiological signals of such organisms, for instance the amplitude of the EEG signals, appear to vary over time in a complex manner. These temporal variations result from intrinsic disturbances and actions, such as the activity of an organism or the process of aging. In physiological signals these fluctuations are non-periodic. In the past years, the properties of the physiological signals used to be described by the mean value, whereas the fluctuations around the mean were discarded as noise. However, research over the recent years revealed that these fluctuations exhibit long-range correlations over many time scales, indicating the presence of self-invariant and self-similar structures. Such structures can be captured with fractal or non-linear analysis.

In the current study, we explore the behavior of the temporal fluctuations that are generated by different emotional states. More specifically, NLD index is used in order to capture the self-similarities of the EEG signals and to explore how they are correlated with the dimensions of valence, arousal and liking. NLD is estimated by

$$\mathrm{NLD} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=2}^{\mathrm{N}} |\mathrm{y_n(i)} - \mathrm{y_n(i-1)}|, \tag{1}$$

where $\mathrm{y_n(i)}$ and N represent the ith sample after amplitude normalization and the length of the signal respectively [8]. NLD index is very accurate and easy to implement and it is related to the actual fractal dimension of the time series through a power law [8].

The other measure of complexity used in this study is NSI, which segments the signals into small parts and estimates the variation of the local averages [9]. NSI is also easy to implement and it is related to the signal's complexity through the fact that it captures the degree of the signal's non-stationarity. The mean values of both NLD and NSI were used to estimate the correlation between EEG fluctuations over time and the subjective ratings of valence, arousal and liking.

2.4 Correlation analysis

For the correlation analysis we computed the Spearman coefficients between the PSD, NLD and NSI features, and the subjective ratings of valence, arousal and liking for each electrode. In terms of the subjective correlation analysis, the most significant electrodes were selected as those with p-value, $p < 0.05$, for each subject. Then the common most significant electrodes were selected by considering independency among the subjects and combining the individual p-values using Fisher's meta-analysis method. Briefly, Fisher's method assumes that a set of p-values obtained from independent studies testing the same null hypothesis may be combined to overally verify the null hypothesis. Finally, subject-independent correlation analysis was performed by treating all subjects as one. Hence, all features were concatenated in one matrix and the significant electrodes were selected as those with $p < 0.05$.

3 Results and Discussion

3.1 Subjective analysis

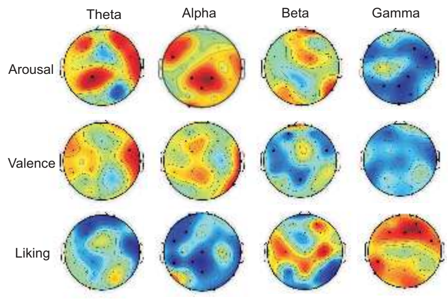
The inter-correlation values between each subject's ratings for valence, arousal, and liking are presented in Table 1. The significant correlations are indicated with a star and they are selected as those with $p < 0.05$. The correlation values between the logarithmic mean PSD and the ratings, mapped into the corresponding brain regions, are presented in Figure 1 for each subject respectively. Significant electrodes are represented by black spots.

Table 1. Inter-correlations between the different dimensions of ratings for each subject.

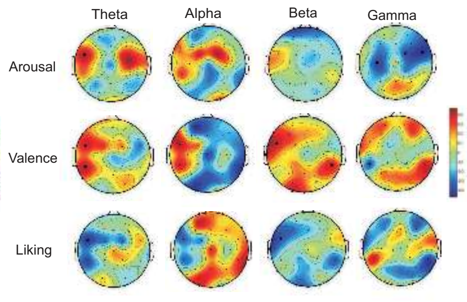
	Subject 1			**Subject 2**			**Subject 3**		
	Valence	Arousal	Liking	Valence	Arousal	Liking	Valence	Arousal	Liking
Valence	1	0.13	-0.46	1	0.33	-0.95*	1	0.75*	-0.77*
Arousal	0.13	1	-0.56*	0.33	1	-0.4	0.75*	1	-0.79*
Liking	-0.46	-0.56*	1	-0.95*	-0.4	1	-0.77*	-0.79*	1
	Subject 4			**Subject 5**			**Subject 6**		
	Valence	Arousal	Liking	Valence	Arousal	Liking	Valence	Arousal	Liking
Valence	1	0.4	-0.41	1	0.55*	-0.5*	1	0.61*	-0.88*
Arousal	0.4	1	-0.12	0.55*	1	-0.94*	0.61*	1	-0.58*
Liking	-0.41	-0.12	1	-0.5*	-0.94*	1	-0.88*	-0.58*	1

Regarding the EEG behavior of different subjects, as can be seen in Figure 1, subject 1 shows the highest correlation between the ratings and the logarithmic mean PSD. For this subject, the maximum correlation value reaches 0.8. Such high correlations appear mainly in theta and alpha bands, indicating positive correlation between logarithmic mean PSD and arousal, as well as between logarithmic mean PSD and valence. High positive correlation also appears in gamma band, between logarithmic mean PSD and liking.

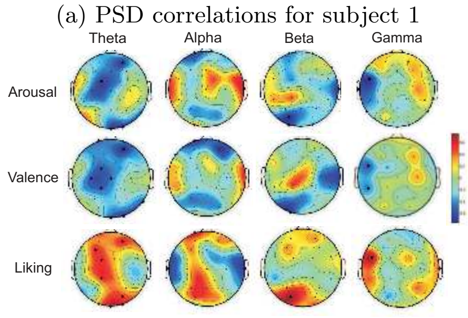
Observing the correlations of the Figure 1(a), it is obvious that arousal and liking follow opposite correlation patterns, especially in theta band. This behavior is certified by the fact that there is significant negative correlation between arousal and liking for the first subject, which is presented in Table 1. Negative correlation between arousal and liking indicates that subject 1 shows preference for music videos that elicit low arousal values regardless of the value of valence.



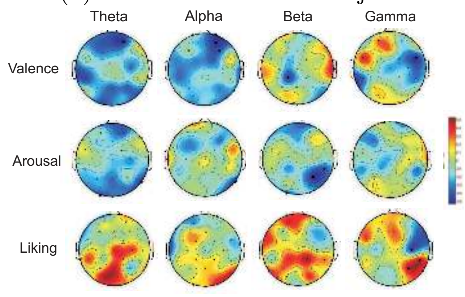
(a) PSD correlations for subject 1



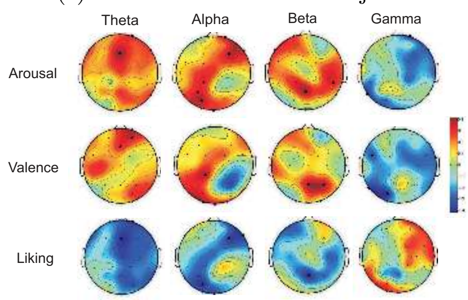
(b)PSD correlations for subject 2



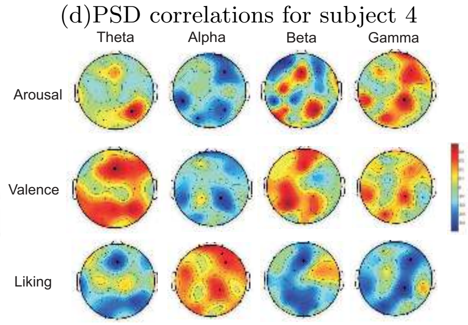
(c) PSD correlations for subject 3



(d)PSD correlations for subject 4



(e) PSD correlations for subject 5



(f)PSD correlations for subject 6

Fig. 1. Brain region mappings of the correlations between the logarithmic mean PSD and the ratings for each subject.

For subject 2, a significant negative correlation value between valence and liking appears, which is clearly presented in Figure 1(b) due to the fact that they are very high (r =0.95). These negative correlations indicate that subject 2 has a preference for music videos that elicit negative values for valence, independent of the values of arousal. For subject 3 there are significant correlations among all ratings, which can be obviously seen in Figure 1(c). More specifically, valence and arousal appear to follow similar correlation patterns, whereas arousal and liking, as well as valence and liking, follow opposite correlation patterns. This behavior indicates that subject 3 prefers music videos that elicit low arousal values and negative valence values (sad videos). Finally, subjects 5 and 6 show similar correlation behavior, indicating that they both prefer music videos that elicit low arousal and negative valence values (sad music video clips), whereas there are no significant inter-correlations among the ratings of subject 4.

Since emotion is a very complex phenomenon and is influenced by different structures, situations and contextual environment, it is expected to see different activated brain regions for different subjects even if their affective states seem to be similar. Nevertheless, there is occasionally some level of affective consistency among the activated brain regions of different subjects. In order to capture these common activated regions, Fisher's meta-analysis method was applied. Fisher's method combines the p-values of independent tests which share the same null hypothesis. The null hypothesis for this case is the hypothesis that the logarithmic mean PSD is uncorrelated with the ratings of valence, arousal and liking for each electrode and subject. Hence, if the null hypothesis is rejected, there must be significant correlations between the logarithmic mean PSD and the corresponding rating, for the specific electrode and subject. The common significant electrodes for all the subjects after applying Fisher's test are presented in Table 2.

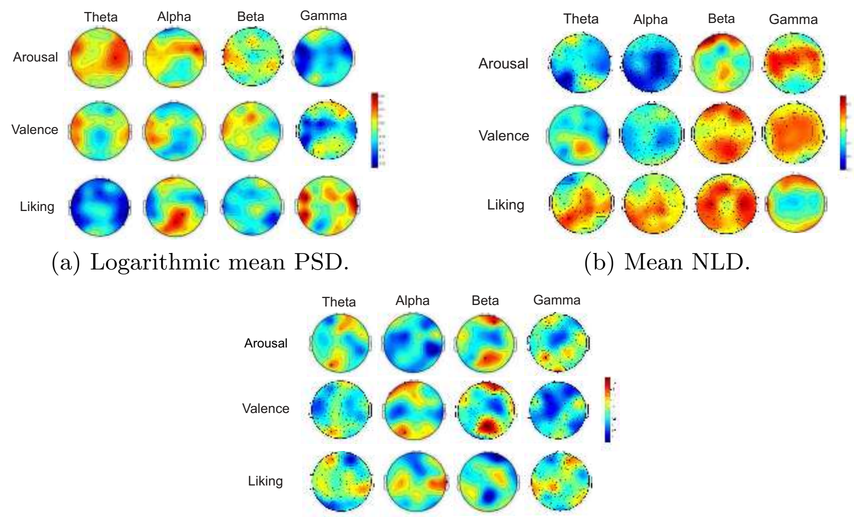
Table 2. Common significant electrodes using Fisher's meta-analysis test.

	Theta	**Alpha**	**Beta**	**Gamma**
Valence	FC1, CP5, P8, CP6 Oz, Fz, F4, AF4	CP6, Oz	O1, Pz, PO4	CP5
Arousal	Fz, PO4, AF4	CP5, Oz, Pz, Cz O2, F8, Fz, F4	O2, Fp1	FC5, CP5, P7 C4, FC2, F8
Liking	-	Fp1, CP5, Oz, O2	-	FC5, CP5, F8, Fz, AF4

As it is shown in Table 2, only 15 electrodes out of 32 show significant activation in the overall affective process, some of which are activated with more than one ratings or for more than one brain bands. For instance, CP5 electrode shows activation with valence, arousal and liking but for different brain bands. Moreover, it is observed that, for all emotion dimensions, the CP5 region is activated in gamma band. Another example is the Fz electrode, which demonstrates activation for valence and arousal in theta band, for arousal in alpha band and for liking in gamma band. Hence, there are some electrodes that show significance for more than one affective dimension (valence, arousal or liking) and for the same brain frequency bands. Therefore, these electrodes might not be able to distinguish the variations in each of the dimensions. If, thus, significant electrodes are used as features to infer for the status of each rating, the analysis should be better based on the electrodes which are exclusively related with one affective dimension for each brain band.

3.2 Subject independent analysis

Subject independent analysis is performed by concatenating all features and ratings in one vector, which from now on will be referred to as overall features and ratings, respectively. The inter-correlations between the overall rating dimensions of valence, arousal and liking are all significant with values $r = 0.6$ for arousal and valence, $r = -0.68$ for valence and liking, and $r = -0.67$ for arousal and liking. The correlations between the overall logarithmic mean PSD and the subjective ratings of valence, arousal and liking are shown in Figure 2(a). Significant electrodes are presented by black spots.



(a) Logarithmic mean PSD. (b) Mean NLD. (c) Mean NSI.

Fig. 2. Brain region mappings of the correlations between the overall frequency and time features with the ratings.

In consistency with the overall subjective ratings, alpha and gamma bands of Figure 2(a) show similar correlation patterns for arousal and valence, and opposite correlations for arousal and liking as well as valence and liking. These significant correlations indicate that subjects had a tendency to prefer music videos that elicit low arousal and negative valence values.

Regarding the analysis of the brain regions of interest, in Figure 2(a) high positive correlation appears between arousal and logarithmic mean PSD in theta band, especially on the right side of the cortex. In alpha band, left dorsolateral prefrontal cortex is activated with arousal, whereas right central region is positively correlated with arousal.

Moreover, left temporal region is positively correlated with arousal in beta band, indicating that the left auditory region is activated when arousal becomes lower and consequently when the subjects are more calm. Since arousal and liking are oppositely correlated, left auditory region in beta band is activated with high liking. This is consistent with the findings of the correlations among the overall subjective ratings. Temporal lobe is also related to memory and understanding of language. Therefore, it is normal that this lobe is activated when liking is high.

Furthermore, in gamma band, somatosensory motor cortex is activated with high arousal, high valence and low liking, indicating that the subjects are willing to move when arousal and valence are high, although this is not necessarily related to whether they like the specific music clip. However, somatosensory motor cortex is also activated with high liking in theta band, regardless of the values of arousal and valence.

Finally, ventral stream of the left lateral parietal lobe shows similar behavior with the somatosensory motor cortex. In particular, it yields activation with high arousal and valence in gamma band, whereas it is being activated with high liking in theta band, independently of the values of arousal and valence. Ventral stream is highly associated with object recognition and form representation, indicating that these processes take place with high arousal and valence in gamma band and with high liking in theta band.

Regarding the analysis in the time domain, the correlations between the overall mean NLD and the subjective ratings are shown in Figure 2(b) and the correlations between the overall mean NSI and the subjective ratings are shown in Figure 2(c). Although NLD does not follow the patterns of the correlations among the overall subjective ratings, these patterns are obviously shown in almost all bands of NSI. In NSI, frontal and parietal cortex seem to be associated with low arousal, negative valence and high liking. More specifically, in alpha and beta bands, frontal lobe is positively correlated with valence and arousal, and negatively correlated with liking, whereas in gamma band frontal lobe is negatively correlated with valence. Considering that frontal lobe is associated with attention, different brain bands of the frontal lobe are activated depending on whether the attention emanates from liking issues or issues associated with high valence.

3.3 Conclusions

In this paper, the changes of EEG signal during different emotions elicited by watching various music video clips were studied. To this end, time domain and frequency domain features of the EEG signal were extracted and the analysis of correlation between these features and subject's self assessed emotions was performed. These self assessments were verified to make sure they are expanded on the arousal-valence plane. Subject-dependent analysis revealed that there are differentiations among the subjects' brain activation patterns, due to the difference in age, personality, different contextual environment and general preferences. Nevertheless, there are similarities regarding the activation of several electrodes, which were captured using Fisher's method. Finally, subject-independent analysis explored the general behavior of the different brain bands, depending on the overall features and ratings. It revealed that frequency and time features are complementary, so they are both needed for the correlation analysis.

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