Affective State Characterization based on Electroencephalography Graph-Theoretic Features

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***Abstract*— Affective states are typically characterized using spectral power information obtained from electroencephalography (EEG) data collected over specific brain regions. However, while experiencing a complex emotional audio-video stimuli, brain networks transfer information in a highly interactive manner. To characterize this information, we propose using graph theoretical features. Towards this end, first, we established graph theoretical features as meaningful correlates of affective states through Pearson correlation. Then we compared the classification performance of these features with that of conventional spectral power features where percentage increases in classification performance of 7% and 11% were found in arousal and valence, respectively. Moreover, feature level fusion was explored and resulted in better performance as compared to the feature sets alone thus, highlighting the complementarity of EEG graph based features and spectral powers. Overall it is hoped that this study will enhance affective state evaluation via passive brain computer interfaces, thus leading to a plethora of applications such as user experience perception modelling and affective indexing/tagging of videos, to name a few.**

I. INTRODUCTION

Burgeoning research in the field of passive brain computer interfaces has led to effortless characterization of an individual's affective states. Affective state characterization forms an integral part of neuromarketing, affective video indexing and, more recently, user experience (UX) or quality-of-experience (QoE) perception modelling. As such any video on demand service provider (e.g., Youtube and Netflix) needs to enhance users' QoE in order to gain competitive edge and succeed. Thus, during the last decade researchers have focussed on developing various QoE quantification schemes. However, inclusion of information from users' affective and cognitive states into these schemes could hugely increase their efficiency, as users' states widely impact QoE perception formation processes. Towards this end, affective state characterization through passive BCIs could aid in building enhanced user-adaptive QoE quantification schemes.

Conventionally, passive BCIs have utilised electroencephalography (EEG) to extract neurophysiological correlates of users' affective states. Generally, the spectral power features derived from several frequency bands, such as delta (δ: 1-4Hz), theta (θ: 4-8Hz), alpha (α: 8-13Hz), beta (β: 13-30Hz) and gamma (γ: 30-50Hz), are used as neurophysiological correlates of emotional activity [1]. Such features encode brain activity over a specific brain region. However, during the time course of watching a music video, several parts of the brain are activated to process and integrate the auditory and visual streams, as well as to evaluate emotional content via attentional and context updating mechanisms. Thus, affective state characterization comprises a complex flow and interplay of information between brain regions that may span different EEG frequency bands.

The flow of information while watching an emotional music video clip can be represented by the model shown in Figure 1. The model consists of a sensory processing block and an affect-cognition processing block. The specialised sensory information is processed in a segregated manner in densely interconnected brain regions of auditory and visual cortices. The processed information is then evaluated through a highly interactive and integrated interplay of information between affective and cognitive neuronal networks [2]. Through top-down effects, these affective-cognitive networks can further influence the analysis, processing, and integration of the multiple sensory streams, thus closing the information flow loop. Within this information flow model, the affect-cognition block plays a crucial role as it not only modulates integrated processing of information, but also influences its segregated processing through top-down effects. These properties of neuronal networks can be quantified using features obtained from graph-theoretical analysis of brain activity [3]. As such, it is expected that improved affective state characterization can be achieved by mapping the flow of information through EEG channels which encode activity of various neuronal networks involved in affect processing. In this paper, we compare the efficiency of graph theoretical features obtained from EEG data with the conventional spectral power features, to characterize and classify user affective states.

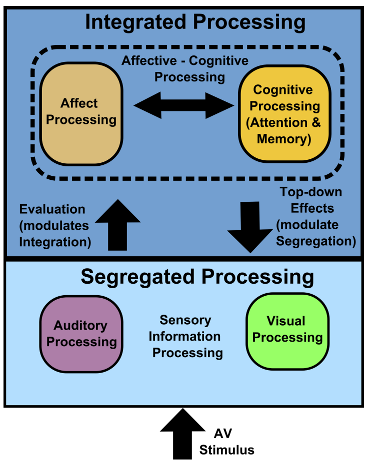

Fig. 1: Information flow model for affect laden audio-video stimuli

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The remainder of this paper is organized as follows: section II show the methods and materials used in our study. Section III and IV show the results and discussion, respectively. Lastly, conlusions are drawn in section V.

II. Materials and Methods

A. Database for Emotion Analysis using Physiological signals (DEAP)

We obtained the pre-processed EEG data along with users' subjective affective ratings from the publicly-available "database for emotion analysis using physiological signals (DEAP)" [4]. The database consists of EEG recordings from thirty two participants (50% females, average age = 26.9 years) while they experienced forty, one-minute long, music videos with emotional content. The EEG data was acquired using a Biosemi ActiveTwo system (Amsterdam, Netherlands), at a sampling frequency of 512 Hz, while placing thirty two electrodes according to international 10-20 system over the scalp. The data was then pre-processed by common referencing, downsampling to 128 Hz, band-pass filtering between 4-45 Hz, and eye blink artifact removal via independent component analysis. For the subjective data, following the presentation of each music video, participants rated their valence and arousal on a discrete 9-point scale using the self assessment manikins (SAM).

B. Feature Extraction

As explained earlier, the neuronal affect processing is a highly interactive brain activity. Therefore, to encode such information various measures have been proposed in the past, one such measure is the magnitude squared coherence (MSC). We have used MSC as measure of synchrony between two EEG electrodes. This measure was extracted for all the pairs of electrodes for different EEG bands, namely, theta ($\theta = 4 - 8$ Hz), low alpha ($l - \alpha = 8 - 10$ Hz), high alpha ($h - \alpha = 10 - 12$ Hz), alpha ($\alpha = 8 - 12$ Hz), low beta ($l - \beta = 12 - 18$ Hz), mid beta ($m - \beta = 18 - 24$ Hz), high beta ($h - \beta = 24 - 30$ Hz), beta($\beta = 12 - 30$ Hz), gamma ($\gamma = 30 - 45$ Hz) and full ($full = 4 - 45$ Hz) bands.

Adjacency matrices (or graphs) were created by thresholding the MSC values between 0.1, 0.2,...0.9, as described in [3]. Following that, graph theoretical features such as clustering coefficient (C) and local efficiency (E_l) were computed, which encode information regarding segregation or local properties of graphs. Characteristic path length (L) and global efficiency (E_g), in turn, were calculated to encode information regarding integration or global properties of graphs. We also extracted the small-worldness (S) properties of the graphs, as human brain networks have been proposed to have evolved a balance between segregation and integration properties resulting in so-called small-world networks [5]. This resulted in 5 graph features per band per threshold. Due to space limitations, an in-depth description of the features is not possible and the interested reader is referred to [3] for complete details. Moreover, for comparison, we also extracted spectral power features for θ, α, β and γ bands at each electrode along with asymmetry features for each band as computed in [4] resulting in 184 features.

C. Neurophysiological Correlates of Affective States

In order to quantify the relationship between the subjective ratings and all the graph-theoretic metrics, Pearson correlation coefficients were used. Correlation coefficients were computed at each of the nine investigated thresholds $(0.1, \ldots, 0.9)$ however, only the thresholds at which significance was achieved were used in the following classification analyses. Furthermore, to investigate if the EEG measures could be used to classify the subjective ratings into 'high' or 'low' categories, hypothesis testing via an unpaired t-test was used. For this, the valence and arousal ratings, which were scored greater than or equal to five were categorized as 'high' and those below five as 'low', and the hypothesis testing was done. These results helped establish the significance of graph theoretical features in characterising affective states.

D. Affective State Classification

Following correlation analysis, the dataset was split into a development and validation set. The development set consisted of 5 'high' and 5 'low' randomly selected points from each subject, resulting in 320 samples. The remaining 960 samples were used in the validation set. The development set was used to rank the features using minimum redundancy maximum relevance (mRMR) algorithm [6], for three different feature sets consisting of: (a) only spectral power and asymmetry features, (b) only graph features and (c) all features together. Then the ranked features were used to classify users' affective states using the validation set, where a feature was introduced in each step and the classification accuracy was computed. The classification was done using leave-one-sample-out cross-validation per subject, similar to the procedure adopted in [4]. For this, we used support vector machine (SVM) classifier using radial basis function (RBF) with $C = 1.0$ and $\gamma = 0.01$, which was implemented using the Scikit-learn library for Python [7].

III. Results

Table I reports the highest significant correlations obtained for each measure. It was observed that significance was only attained at thresholds between 0.2 and 0.5, thus resulting in 200 features which were used for classification analyses. Also, using t-test it was found that all measures reported in Table I were able to significantly differentiate between the two category groups, except those indicated by an asterisk. In order to visualize the significant differences between the 'high' and 'low' categories, as well as the interplay between the integration and segregation modules, Figure 2 depicts scatter-plots of E_l vs. E_g computed from the MSC connectivity measure with a threshold of 0.4 for arousal. The plots show the average metric values, as well as their standard error bars. Moreover, the classification results for valence and arousal are shown graphically in Figures 3 (a-b), respectively. Table II, in turn reports the maximum accuracy achieved using each feature set along with the number of top features needed to reach that level of performance.

TABLE I: Significant ($p < 0.05$) correlations between subjective ratings ('Val' - Valence, 'Aro' - Arousal) and EEG graph-theoretic measures. Superscripts in the table indicate the threshold at which highest coefficient was attained. A dash ($-$) indicates that significant correlations could not be found at any of the investigated thresholds. An asterisk, in turn, indicates a measure that obtained insignificant differences between low and high categories.

Subjective Dimension (MSC Band)	L	E_g	C	E_l	S
Val ($l-\alpha$)	-0.45^3	$-$	$-$	0.35^4	$-$
Val ($h-\alpha$)	-0.48^3	0.45^5	0.41^2	0.41^5	0.43^4
Val (α)	-0.48^4	0.39^5	0.38^5	0.41^5	0.37^3
Val ($l-\beta$)	-0.41^3	0.44^5	0.41^4	0.41^4	0.34^3
Val ($m-\beta$)	$-$	$-$	0.32^3	0.36^3	$-$
Val (β)	-0.36^3	0.32^4	0.32^4	0.37^4	$-$
Val (γ)	$-$	0.36^5	$-$	$-$	$-$
Aro ($l-\theta$)	0.43^2	-0.40^2	-0.32^3	-0.35^3	-0.36^2
Aro ($l-\alpha$)	-0.38^{2*}	0.38^{2*}	0.40^2	0.39^{2*}	0.43^4
Aro ($l-\beta$)	-0.44^2	0.47^2	0.46^2	0.40^2	0.50^3
Aro ($m-\beta$)	-0.63^2	0.64^2	0.70^2	0.71^2	$-$
Aro ($h-\beta$)	-0.65^2	0.63^3	0.60^4	0.61^2	0.59^{2*}
Aro (β)	-0.64^2	0.66^3	$-$	$-$	0.57^2
Aro (γ)	-0.51^{2*}	0.53^3	0.52^3	0.50^3	0.47^{2*}
Aro ($full$)	-0.65^3	0.57^4	0.60^{2*}	0.54^4	0.57^{2*}

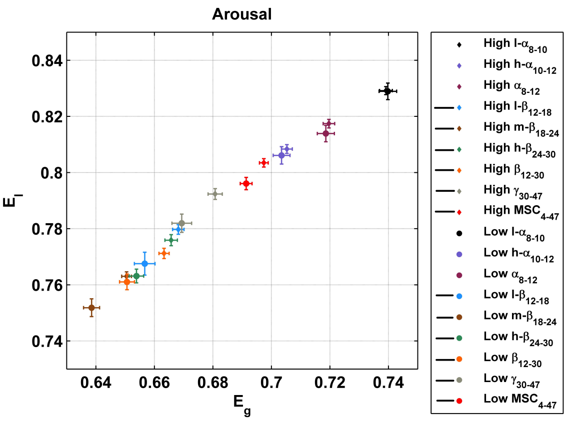


Fig. 2: Scatterplot of E_l vs. E_g for subjective arousal. Significant differences between the low and high categories are represented by a '$-$' in the legends

IV. Discussion

A. Neurophysiological Correlates

The results presented in Table I show that L is inversely related to the subjective ratings, whereas E_g, E_l, C and S are all positively correlated. A decrease in L and an increase in E_g points towards an increase in sequential and parallel global information flow, thus leading to greater integration of information in brain connectomes [3]. On the other hand, an increase in C and E_l suggests an increase in efficiency of local information flow or segregation in brain connectomes.

In fact, salient stimuli are known to induce high arousal levels [8], thus leading to more integrated processing of information via the so-called 'workspace neurons,' as proposed by the global workspace theory [2]. Also, the increase in segregation for brain connectomes may be due to the fact that increased salience may lead to an increase in processing of cognitive states, such as attention, which have a top-down effect on the sensory information processing [9]. Combined, these two results lead to an overall increase in small-worldness properties with increasing arousal. The subjective arousal rating, specifically, showed stronger positive correlations in higher frequency bands (e.g., $f \geq 18Hz$) using MSC, along with moderate correlations for $f < 18$. The higher involvement of faster rhythms in high arousal states have been observed in previous studies [10], [11]. On the other hand, for the theta band, efficiency parameters derived from inter-electrode MSC showed negative correlation with arousal. This can be due to decrease in theta band coherence in the right hemisphere, during affect perception [10].

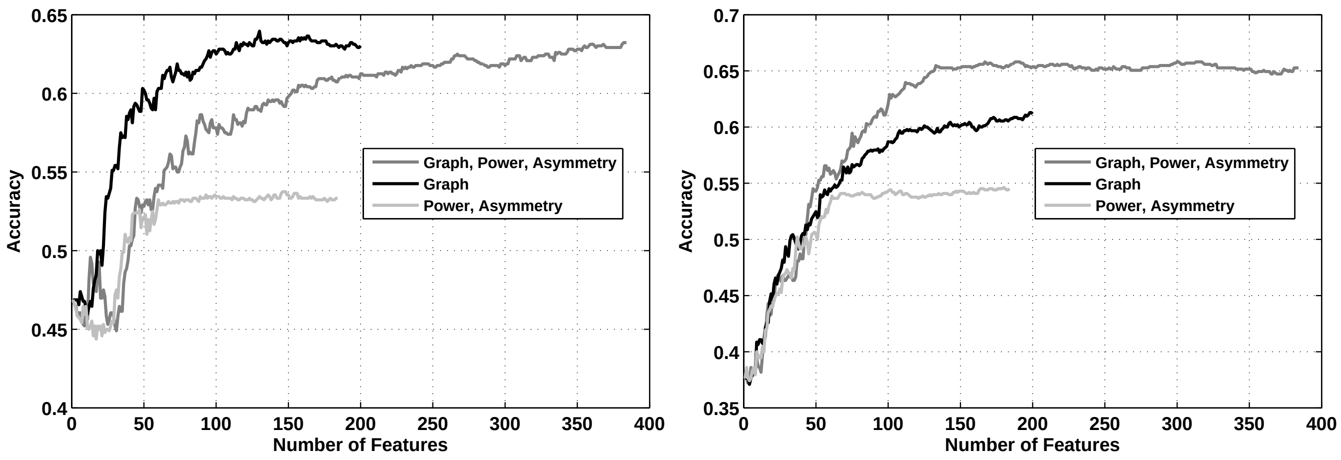
Moreover, the graph metrics derived from MSC$_\alpha$, MSC$_\beta$ and MSC$_\gamma$ were shown to be significantly correlated with the subjective valence rating. A recent study [3], has suggested that in lower frequencies, pleasant visual stimuli require shorter L (global properties). We have found similar results not just for lower frequency bands, but also for higher frequency bands. Furthermore, we also found a significant increase in local properties of the brain networks in the mid-beta frequency range. Various studies have shown that the beta band (and its sub-bands) encodes affect related information. For example, in [12] a decreased intra-hemispheric left coherence in the low beta band with negative affect was reported and in [13] an asymmetric activation of the beta band while attending to affective visual stimuli was shown. Thus, we can state that the graph features encode meaningful affect related information as the observed correlations partially concur with some of the previous studies, and can be used as valid features for affective state recognition.

B. Affect Classification

From Figures 3 (a) and (b) it can be observed that the accuracy curves generally stabilize around the maximum levels, reported in Table II, after the addition of certain number features. Thus, it can be stated that graph features achieve better classification accuracy as compared to spectral

TABLE II: Maximum valence and arousal classification accuracy along with the number of top features needed to achieve such accuracy.

Feature Set	Subjective Dimension	Maximum Accuracy	Number of Features
Spectral Power, Asymmetry	Valence	52%	60
	Arousal	54%	70
Graph	Valence	63%	135
	Arousal	61%	130
Spectral Power, Asymmetry, Graph	Valence	63%	350
	Arousal	66%	167



(a) (b)

Fig. 3: Classification performance versus number of top features for different feature sets for (a) valence and (b) arousal

power and asymmetry features, for both valence and arousal. Generally, the spectral power features lack information regarding interactions between brain regions however, the asymmetry features encode only inter-hemispheric interactions. Graph features, on the other hand, encode information regarding dynamics of information transfer throughout the brain, thus outperforming the conventional features used for affect classification. Also, fusion of graph theoretical features with spectral power and asymmetry feature sets result in a classification accuracy which is better (i.e., for arousal) than or equal (i.e., for valence) to the best performance achieved by these feature sets alone. However, to achieve this performance the feature fusion set would require a larger number of features, as shown in Table II. Furthermore, amongst the top features from each feature set, most of them belonged to beta (33%) and alpha (30%) band followed by theta and gamma bands. This result is in corroboration with our findings reported in Table I, where alpha and beta bands showed the highest significant correlations with the subjective ratings. Also, most of the top features from graph theoretical feature set belonged to the threshold of 0.2 (35%), which again concurs with our findings in Table I.

V. CONCLUSIONS

In this paper, we have proposed the use of graph theoretical features to characterize users' affective states while they experience music videos with different emotional content. The graph features were shown to outperform conventional features, such as spectral power and asymmetry, to solve the affective state classification problem. Also, fusion of graph features along with the conventional features was shown to improve performance, thus suggesting complementarity between the two features. These results are expected to aid in better modelling of users' experience perception, ultimately resulting in better user-adaptive services.

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