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KOELSTRA, Sander, *et al.*

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Reference

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Single Trial Classification of EEG and Peripheral Physiological Signals for Recognition of Emotions Induced by Music Videos

Sander Koelstra[1], Ashkan Yazdani[2], Mohammad Soleymani[3], Christian Mühl[4], Jong-Seok Lee[2], Anton Nijholt[4], Thierry Pun[3], Touradj Ebrahimi[2], and Ioannis Patras[1]

[1]Department of Electronic Engineering, Queen Mary University of London
[2] Multimedia Signal Processing Group, Ecole Polytechnique Fédérale de Lausanne
[3] Computer Vision and Multimedia Laboratory, University of Geneva
[4]Human Media Interaction Group, University of Twente
{sander.koelstra,ioannis.patras}@elec.qmul.ac.uk
{ashkan.yazdani,jong-seok.lee,touradj.ebrahimi}@epfl.ch
{mohammad.soleymani,thierry.pun}@unige.ch
{muehlc,a.nijholt}@ewi.utwente.nl

Abstract. Recently, the field of automatic recognition of users' affective states has gained a great deal of attention. Automatic, implicit recognition of affective states has many applications, ranging from personalized content recommendation to automatic tutoring systems. In this work, we present some promising results of our research in classification of emotions induced by watching music videos. We show robust correlations between users' self-assessments of arousal and valence and the frequency powers of their EEG activity. We present methods for single trial classification using both EEG and peripheral physiological signals. For EEG, an average (maximum) classification rate of 55.7% (67.0%) for arousal and 58.8% (76.0%) for valence was obtained. For peripheral physiological signals, the results were 58.9% (85.5%) for arousal and 54.2% (78.5%) for valence.

1 Introduction

Given the enormous amounts of untagged video data available on the web nowadays, the need for automatic categorization and tagging of video content to enable efficient indexing and retrieval is evident. Up to this date, the most widespread method for tagging video data is through manual explicit annotation. This is a slow and cumbersome procedure and cannot keep up with the growing amount of created data. An alternative for this method is to automate the tagging procedure. Recently, considerable progress has been made towards automatic content-based tagging with acceptable accuracy under restrictive conditions and for specific domains. However, research in this area has shown that it is not feasible to fully automate the process for general video tagging in the foreseeable future due to the existence of the semantic gap.

Emotional tags associated with the video content can play a significant role for indexing and retrieval purposes. For instance, they can be used in efficient retrieval of video content that is in consonance with the affective mood and state of the users. Therefore, extracting emotional tags implicitly by studying the affective states of the users and assigning these as metadata to video content allows the personalization of the content delivery. One approach to analysis and recognition of emotions is to directly assess the activity of the central nervous system, specifically brain electrical activity, and study the changes in this activity as the user experiences different emotional states. Several works exist that are related to emotion recognition from electroencephalogram (EEG) [7, 14, 10, 2]. Furthermore, there are a number of experiments pointing to the fact that physiological activity is not an independent variable in autonomous nervous system patterns but reflects experienced emotional states with consistent correlates[1, 17].

To the best of our knowledge, this is the first work using music videos as stimulus material. The possibility of contradictory information received from visual and auditory modalities makes this particularly challenging.

There has been a large number of published works in the domain of emotion recognition from physiological signals [11, 2, 18]. Amongst these studies, few of them studied EEG signals and achieved notable results using video stimuli. Lisetti and Nosaz used peripheral physiological response to recognize emotion in response to movie scenes [11]. The movie scenes elicited six emotions, namely sadness, amusement, fear, anger, frustration and surprise. They achieved a high recognition rate of 84% for the recognition of these six emotions. However the classification was based on the analysis of the signals in response to pre-selected segments in the shown video known to be related to highly emotional events.

Kierkels et al. [5] proposed a method for personalized affective tagging of multimedia using physiological signals. Valence and arousal levels of participants' emotion when watching videos were computed from physiological responses using linear regression. Quantized arousal and valence levels for a video clip were then mapped to emotion labels. This mapping gave the possibility to retrieve video clips based on keyword queries. So far this novel method achieved low precision.

Yazdani et al. [19] proposed a brain computer interface (BCI) based on P300 evoked potentials to emotionally tag videos with one of the six basic emotions proposed by Ekman [4]. Their system was trained with eight subjects and then tested on four other subjects. They achieved a high accuracy on selecting tags. However, in their proposed system, a BCI only replaces the interface for explicit expression of emotional tags. The method does not implicitly tag a multimedia item using the subject's behavioural and psycho-physiological responses.

In this paper, the EEG and biological signals are acquired from six subjects as they watch different music videos and methods for automatic recognition of the user's affective states are presented. The rest of the paper is organized as follows. Section 2 introduces the methodology used in this study including test material selection, data acquisition and data processing. Experimental results are presented and discussed in Section 3 and Section 4 concludes the paper.

2 Methodology

We use the valence-arousal scale proposed by Russell [15], which has been widely used in research on affect, in order to quantitatively describe emotion. In this scale, each emotional state can be placed on a two-dimensional plane with arousal and valence as the horizontal and vertical axes. Arousal can range from inactive (e.g. uninterested,bored) to active (e.g. alert, excited), whereas valence ranges from unpleasant (e.g. sad, stressed) to pleasant (e.g. happy, elated). In the following sections, the procedures of test material selection and physiological data acquisition and processing will be explained.

2.1 Subjective Test and Data Selection

The first step of our work is to compile a test set of music videos for physiological data acquisition. The objective of the selection procedure is to ensure that clips inducing various levels of valence and arousal are included in the final data set.

We first manually collected 70 candidate music videos spanning diverse genres, ages, and styles. From this collection, the final set of 20 test videos were chosen using a web-based subjective emotion assessment interface. Participants watched video clips one by one and rated them on a discrete 9-point scale for each of valence and arousal, as shown in Fig. 1. Each subject watched 17 clips and, on average, each video clip was rated by 11 subjects.

Fig. 2(a) shows the ratings, averaged over the test subjects, plotted on the valence-arousal plane. The plane is divided into five regions: positive valence and positive arousal (V_+A_+), positive valence and negative arousal (V_+A_-), negative valence and positive arousal (V_-A_+), negative valence and negative arousal (V_-A_-), and neutral (N). For each of the five regions, the four video clips showing the largest discriminability from the other four regions were chosen for inclusion in the test set. In the V_-A_+-region, only two video clips were available and thus each of them was split into two parts that were separately used in the experiments.

The first two minute portions of the selected 20 videos were used for the data acquisition.

2.2 Data Acquisition

The experiments were performed in a laboratory environment with controlled temperature and illumination. EEG and peripheral physiological signals were recorded using a Biosemi ActiveTwo system[1] on a dedicated recording laptop (Pentium M, 1.8 GHz). Stimuli were presented on a dedicated stimulus laptop

[1] http://www.biosemi.com

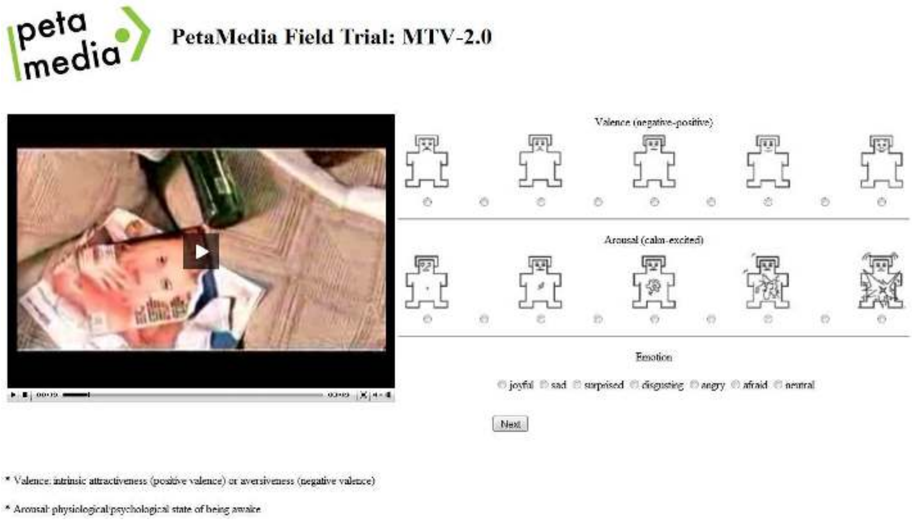


Fig. 1. Screenshot of the web interface for subjective emotion assessment.

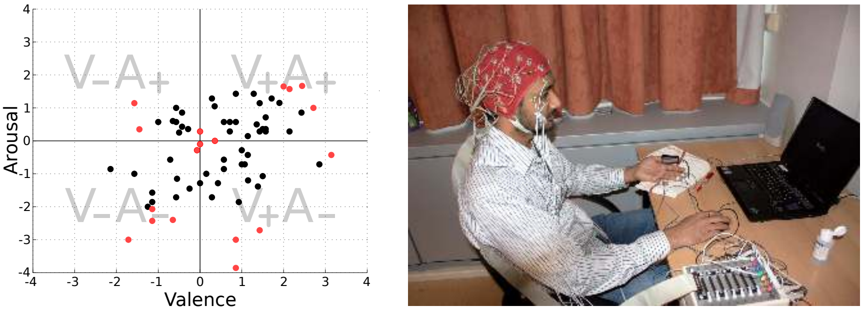
(P4, 3.2GHz) that sent synchronization markers directly to the recording PC. For displaying the stimuli and recording the user's ratings the software "Presentation" by Neurobehavioral systems[2] was used. In order to minimize eye movements, all video stimuli were shown with a width of 640 pixels, filling approximately a quarter of the screen. 32 active AgCl electrodes were used (placed according to the international 10-20 system) and the EEG data was recorded at 512 Hz. At the same time, 13 peripheral physiological signals (which will be introduced in section 2.4) were also recorded.

Six participants were asked to view the 20 selected music videos, displayed in a random order. Before the experiment a 2 minute baseline recording was made and before each trial (video) a 5 second 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 in the single trial classification. Fig. 2(b) shows a participant shortly before the start of the experiment.

2.3 Data Processing for EEG Signals

Correlation analysis For the investigation of the correlates of the subjective ratings with the EEG signals, the EEG data was referenced to the common average, re-sampled to 256 Hz, and high-pass filtered with a 0.5 Hz cutoff-frequency using EEGlab[3]. Eye movement and blinking artefacts were removed with a blind

[2] http://www.neurobs.com
[3] http://sccn.ucsd.edu/eeglab/



(a) (b)

Fig. 2. (a) Division of the valence-arousal plane into 5 different regions. The chosen clips from each region are shown in light red. (b) A participant shortly before the experiment.

source separation technique from the AAR toolbox[4] for EEGlab. Then the signals from the last 30 seconds of each trial (video) were extracted for further analysis. To correct for stimulus-unrelated variations in power over time the EEG signal from the five seconds before each video was used as a baseline.

The frequency power of trials and baselines between 2 and 40Hz was extracted with Welch's method with windows of 256 samples. The baseline power was then subtracted from the trial power, yielding the change of power relative to the pre-stimulus period. These changes of power were then Spearman correlated with the valence ratings. This was done for each subject separately and the six p-values per frequency and electrode were then combined to one p-value via Fisher's method [12].

Classification analysis For the single trial classification of the EEG data, a five second baseline before each trial was subtracted from the data and it was referenced to the common average (CAR). The data was down-sampled to 100Hz and bandpass-filtered between 0.5 and 35Hz to remove DC drifts and suppress the 50Hz power line interference. Two different feature extraction methods were compared: power spectral density (PSD) and common spatial patterns (CSP).

A PSD analysis concerns the spectral domain and investigates the rhythmic activity of brainwaves. The power in each of the frequency bands was calculated using the Fourier transform of the signal. Often, the delta theta, alpha, beta and gamma wave bands are used, but here we tried different fixed bandwidths (from 1 to 10Hz) with 50% band overlap. We also included the difference in band power between every pair of electrodes as features.

CSP was originally proposed by Koles [8]. It is a technique to decompose the EEG signal into a number of components based on the variance of the signal that

[4] http://www.cs.tut.fi/g̃omezher/projects/eeg/aar.htm

takes into account the class labels. In brief, it attempts to extract components for which the variance is maximal for one class and minimal for the other. Then, for a new, unclassified signal, one uses the variance of the components as features to classify the signal as belonging to one of the classes. For details, the reader is referred to [8].

2.4 Data Processing for Peripheral Physiological Signals

The following peripheral nervous system signals were recorded: galvanic skin response (GSR), respiration amplitude, skin temperature, electrocardiogram, blood volume by plethysmograph, electromyograms of Zygomaticus and Trapezius muscles, and electrooculogram (EOG). GSR provides a measure of the resistance of the skin by positioning two electrodes on the distal phalanges of the middle and index fingers. This resistance decreases due to an increase of perspiration, which usually occurs when one is experimenting emotions such as stress or surprise. Moreover, Lang et al. discovered that the mean value of the GSR is related to the level of arousal [9].

A plethysmograph measures blood volume in the participant's thumb. This measurement can also be used to compute heart rate (HR) by identification of local maxima (i.e. heart beats), inter-beat periods, and heart rate variability (HRV). Blood pressure and heart rate variability correlate with emotions, since stress can increase blood pressure. Pleasantness of stimuli can increase peak heart rate response [9]. In addition to the HR and HRV features, spectral features derived from HRV were shown to be a useful feature in emotion assessment [13].

Skin temperature was also recorded since it changes in different emotional states. The respiration amplitude was measured by tying a respiration belt around the abdomen of the participant. Slow respiration is linked to relaxation while irregular rhythm, quick variations, and cessation of respiration correspond to more aroused emotions like anger or fear.

Regarding the EMG signals, the Trapezius muscles (neck) activity was recorded to investigate the possible head movements during music listening. The activity of the Zygomaticus major was also monitored, since this muscle is active when the user is laughing or smiling. Most of the power in the spectrum of an EMG during muscle contraction is in the frequency range between 4 to 40 Hz. Thus, the muscle activity features were obtained from the energy of EMG signals in this frequency range for the different muscles. The rate of eye blinking is another feature, which is correlated with anxiety. Eye-blinking affects the EOG signal and results in easily detectable peaks in that signal.

In total 53 features were extracted from peripheral physiological responses based on the proposed features in the literature [2, 18]. A summary of the features is given below.

GSR: Mean and standard deviation of skin resistance, mean of derivative, mean of absolute of derivative, mean of derivative for negative values only (mean decrease rate during decay time), proportion of negative samples in the derivative vs. all samples, spectral power in the bands (0-0.1Hz, 0.1-0.2Hz, 0.2-0.3Hz, 0.3-0.4Hz)

Blood volume pressure: Mean and standard deviation of HR and its derivative, HRV, mean and standard deviation of inter beat intervals, energy ratio between the frequency bands 0.04-0.15Hz and 0.15-0.5Hz, spectral power in the bands (0.1-0.2Hz, 0.2-0.3Hz, 0.3-0.4Hz), low (0.01-0.08Hz), medium (0.08-0.15Hz) and high (0.15-0.5Hz) frequency components of HRV power spectrum.
Respiration: Mean respiration signal, mean of derivative (variation of the respiration signal), standard deviation, range or greatest breath, breathing rate, spectral power in the bands (0-0.1Hz, 0.1-0.2Hz, 0.2-0.3Hz, 0.3-0.4Hz)
Skin Temperature: Range, mean, standard deviation, mean of its derivative, spectral power in the bands (0-0.1Hz, 0.1-0.2Hz, 0.2-0.3Hz, 0.3-0.4Hz)
EMG and EOG: Eye blinking rate, energy, mean and variance of the signal.

Normalization was applied on each feature separately by subtracting the minimum and dividing by the difference between the maximum and the minimum value of the features. The normalization parameters, maximum and minimum values, were obtained from the training set.

3 Results

In this section, we present the results of the methods introduced earlier. First, an analysis on the validity of the self-assessment of participants is presented. Next, we investigate the average correlations between these ratings and observed EEG frequency power. Finally, the results of single trial classification using EEG and peripheral physiological signals are presented.

3.1 Analysis of Subjective Ratings

To validate the affect induction approach and identify possible threats to reliability (e.g. due to extreme habituation or fatigue), we computed the (Spearman) correlations between the rating scales and the stimulus order.

Table 1. The correlations between the rating scales of valence, arousal, like/dislike and the order of the presentation of stimuli. Significant correlations are indicated by stars.

	Valence	**Arousal**	**Like/Dislike**	**Order**
Valence	1	0.46*	0.66*	-0.24
Arousal	-	1	0.56*	-0.17
Like/Dislike	-	-	1	-0.18
Order	-	-	-	1

The correlation analysis revealed a medium correlation between the ratings on the valence, arousal, and like/dislike scales (Table 1). That could be due to the fact that people liked positive emotions evoking and arousing clips more.

Despite the correlations between valence, arousal, and like/dislike, the results suggest that subjects did differentiate between these concepts.

Furthermore, no significant correlation between stimulus order and the ratings was observed. This indicates that any effects of habituation and fatigue were kept to an acceptable minimum.

3.2 Correlations Between EEG Frequencies and Ratings

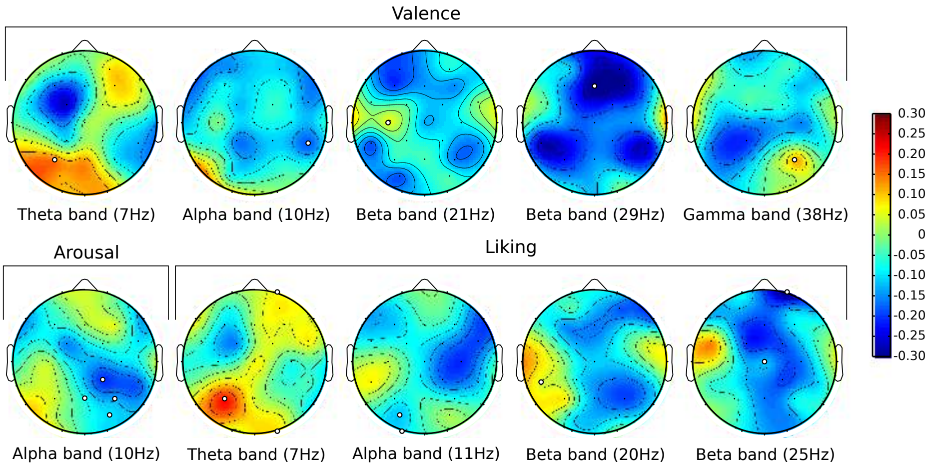


Fig. 3. The plots show the mean correlation coefficients over all 6 subjects for specific narrow frequency bands. Electrodes showing highly significant ($p < 0.01$) differences are highlighted.

The results of the correlation analysis between participant ratings and EEG frequency power suggest that brain activity from different regions of the scalp can be related to the subjective emotional states of the participants along the axes of arousal and valence, and to their preference for the clips (Fig. 3). The large number of tests computed may lead to an increase in false positives. To attenuate this risk, only highly significant ($p < 0.01$) correlations are discussed.

For valence a strong positive correlation with left parietal-occipital power in the theta band, and a negative correlation with right posterior alpha power is observed. This pattern of increasing low frequency band and decreasing alpha band power can be understood in the context of emotion regulation and increased sensory processing [6]. Furthermore, a left central increase and a right frontal decrease in high beta band power is visible with higher valence. Especially, the frontal response might indicate a relative deactivation of cortical regions related to negative mental states [3]. Additionally, a positive correlation with right posterior gamma is observed, possibly hinting again to a role of right posterior cortices in emotion-related sensory processes.

For states of higher arousal, a robust decrease of right posterior alpha power can be observed. This is consistent with the role of (posterior) alpha in sensory processes, and the role of the right hemisphere in affective processing [3].

Like/dislike shows a similar positive correlation in the theta range and negative correlation in the alpha range as observed for valence. This is presumably due to the correlations seen between the valence and like/dislike ratings. Interestingly, a decrease of beta power with higher liking is observed over the central cortical region, known to be involved in imaginary and real (foot) movement [16].

3.3 EEG Single Trial Classification

In both the EEG and peripheral physiological signal single trial classification, the same ground truth labels and classification methods were used. Three different targets were classified: the like/dislike, arousal and valence ratings. We have posed the problem as a two-class classification problem. The given ratings were thresholded (at the centre of the 9-point rating scale) into two classes for each classification target. For the arousal and general rating targets, we had to exclude participant 1, as this participant assigned 17/20 videos a high arousal rating and 19/20 videos a high like/dislike rating. As a result, we did not have enough samples to train the classifier for low arousal and low like/dislike rating for this participant. All other participants rated the videos in a more balanced manner. To improve statistical accuracy of the classification, each trial (video) was split into ten 12-second segments. Testing was done using leave-one-trial-out cross-validation. A linear support vector machine (SVM) was used for classification.

As mentioned before, in the EEG single trial classification, we compared two different feature extraction methods for feature extraction from the EEG signals, PSD and CSP. With the PSD method, we tested several options for the width of the frequency bands (1,2,3,4,5 and 10Hz). Only the results of the best scoring bandwidth are reported. The results of each algorithm and each classification target are given in Table 2 and discussed below.

Table 2. Single trial two-class classification rates for the valence, arousal and like/dislike targets.

Target	**Method**	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**Avg.**
Valence	PSD (3Hz bands)	59.0	45.0	63.0	51.5	58.5	76.0	58.8
	CSP (2 comp.)	60.0	38.5	54.0	60.0	65.0	75.0	58.8
Arousal	PSD (10Hz bands)	—	19.5	67.0	63.5	56.5	53.5	51.9
	CSP (2 comp.)	—	44.5	55.0	65.0	59.5	54.5	55.7
Like/Dislike	PSD (4Hz bands)	—	54.0	50.5	57.5	32.5	52.5	49.4
	CSP (4 comp.)	—	53.0	54.0	63.5	17.0	56.5	48.8

Valence The performance for valence prediction is better than for arousal prediction. For CSP using two components gave the best result. The best result for the PSD method was obtained using 3Hz frequency bands (with 50% overlap). Overall, both algorithms lead to the same classification accuracy (58.8%). Participant 2 scores badly, when excluding this participant, CSP scores 62.8% vs. 61.6% for the PSD method.
Arousal For CSP two components were used and for PSD 10Hz frequency bands. Overall, CSP outperforms the PSD method (55.7% vs. 51.9%). For participant 2, the result is very low for both methods. When excluding this participant, CSP has a mean classification rate of 58.5% vs. 60.0% for PSD.
Like/dislike For CSP four components were used and for PSD 4Hz frequency bands. The PSD method obtains the highest classification accuracy, though the difference is minimal (49.4% vs. 48.8%). Participant 5 had a very low accuracy for both methods. When excluding this participant, CSP outperforms the PSD method (56.8% vs. 53.6%). We are currently investigating the possible causes and remedies of the surprisingly low scores for some of the participants.

3.4 Peripheral Physiological Signals Single Trial Classification

As mentioned earlier, 53 features were extracted from each physiological signal sample. The classification scheme remains the same as for EEG-based classification. The fast correlation based filter (FCBF) feature selection method was used to select the most discriminating features at each iteration of cross-validation[20].

Table 3. Classification rates using an SVM classifier and FCBF feature selection

Target	P1	P2	P3	P4	P5	P6	Avg.
Valence	40.5	37.0	78.5	40.5	65.5	63.0	54.2
Arousal	—	44.5	85.5	55.0	49.0	60.5	58.9
Like/Dislike	—	73.0	69.0	55.5	32.0	60.0	57.9

The classification rates for valence, arousal and like/dislike are given in Table 3. On average, valence results using peripheral physiological signals are worse than like/dislike and arousal. Arousal relates most to peripheral nervous system activities; therefore, the best classification results were obtained for arousal classification. All the results of participant 3 are shown to be amongst the best obtained results. This may be due to a better self-assessment for this participant.

4 Conclusion

In this paper an experiment was conducted to automatically recognize emotions induced by watching music video clips. Six subjects were asked to watch 20 music videos each and rate them according to perceived levels of valence, arousal and general like/dislike. As they watched the videos, their EEG and peripheral physiological signals were recorded.

On average, frequency power over several cortical regions correlated to the subjective state and preferences of the participants, especially in the lower frequencies (i.e. in the theta and alpha bands). Similar findings have been reported in the literature on neurophysiological affective responses.

For single trial classification, We posed the affect recognition problem as a two-class classification problem, classifying the videos as having low or high arousal, valence and like/dislike. We presented results for classification of both EEG and peripheral physiological signals. For EEG classification, the average (maximum) classification rates are 55.7% (67%) for arousal, 58.8% (76%) for valence and 49.4% (63.5%) for like/dislike ratings. Using peripheral physiological responses, the average (maximum) classification rates are 58.9% (85.5%) for arousal, 54.2% (78.5%) for valence, and 57.9% (73%) for like/dislike rating. Due to the low number of samples we could not validate the significance of our results. We are currently repeating the experiment with 20-30 subjects and 40 samples each in order to gain more statistically valid results.

The classification based on arousal and valence values and binary thresholding proved to be rather challenging. The use of music videos may lead to mixed emotional messages from the video and audio modalities. Furthermore the affect-related responses could be specific to the modality the affect was induced by. These effects may complicate any classification. We intend to investigate the influence of the different modalities in our next study.

The results of the single trial classification show that there is a relatively large amount of information in both EEG and peripheral physiological signals regarding users' emotional states. In future work, we aim to create a more extensive video clip database so that they can elicit stronger and more diverse emotions in participants and thus increase the accuracy of the emotion recognition. Furthermore, we plan to fuse the peripheral physiological and EEG modalities in order to better exploit the relative strengths of each modality.

5 Acknowledgment

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