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Emotion Recognition by Physiological Signals

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Abstract

Recently, User's effective state automatic recognition has become a popular research area. It has many applications ranging from health, education, and personalization. In this paper, emotional state arousal and valence induced by watching video clips are identified by physiological and electroencephalogram (EEG) signals by . After each clip subjects had to assess their feelings about the clip. After doing the first part of data analysis we got robust correlations between users' self-assessments of arousal and valence. EEG observations were used to train the classifiers for valence recognition and electrocardiogram ECG observations were used for arousal recognition respectively. We achieved averaged results of 71.6% for valence classification for two states and 54.0% for arousal classification for three states.

Introduction

Significant developments of new sensing techniques and pattern recognition methods have stimulated a growing investigation in the field of affective computing. A latest but fast progressing research filed that focuses on making applications is the user's emotions. In this perspective, affect recognition becomes the key to build systems that automatically react to a user's emotional state in order to enrich the quality of the interaction.

Emotion is a psycho-physiological procedure that activated by cognisant and/or incognisant perception of an article or situation. It is associated with temper, personality, character, disposition, and inspiration. Emotions perform a significant part in personal or social communication and can be conveyed verbally by expressive words or expressed by non-verbal signs such as facial expressions and gestures. Most of the modern Human Computer Interaction (HCI) platforms are lacking in translating the human emotional states to derive the right actions to execute. The main goal of this research paper is to narrow down the gap by efficiently detecting emotional states that can help to enrich the HCI systems in the 21st century.

According to [1], Physiology is defined as "any research in which the dependent variable (the subject's response) in a physiological measure and the independent variable (the factor manipulated by the experimenter) a behavioural one". Physiological parameters include heart rate, respiration rate, and skin temperature. As these parameters reply to signals from the instinctive nervous system as they are not under conscious control.

There has been a significant amount of research work published in the field of emotion recognition by exploiting physiological signals [2-9]. Only a few of these studies achieved prominent results using video stimuli. Lisetti et al. [5] explored physiological responses to detect emotions in movie scenes. The selected movie scenes were used to elicit six basic emotions, namely amusement, sadness, fear, frustration, anger and surprise. A system for personalized affective tagging of video using physiological signals is proposed by Kierkels et al. [6]. Another approach [7] based on linear regression were used to measure arousal and valence levels of participants' emotions when watching videos. Quantized valence and arousal levels for a video were used to map emotion labels. Yazdani et al. [8] used a brain computer interface (BCI) to emotionally tag videos with one of the six Ekman basic emotions [9]. Koelstra et al. [6] used electroencephalogram (EEG) and peripheral physiological signals for emotional tagging of music videos.

In games, a combination of different bio signals is often used to detect emotional state. Takahashi et al. [10] and Rani et al. [11] produced a game that was established to improve player efficiency by adapting the level of difficulty to player's physiological state. Besides these attempts, a number of biofeedback games have recently been developed, which have some integration of a player's physiological data into the game [12]. These games, however focus on stress manipulation rather than optimization of gameplay experience. Emotion detection and recognition are utilized in the treatment of different diseases [13] like Alzheimer, Autism, and Dementia etc.

EEG demonstrates greater prospective to recognize emotions, but with the stationary system with complex and nonrealistic setup that is cumbersome for subjects. Similarly electrocardiogram (ECG) can be a potential signals to detect emotions, but again the complexity and non-real interface does not provide elicit emotion in real life environment. We proposed to exploit non-invasive, wireless EEG and ECG sensors because of advantages in usability in daily life and to capture signals close to natural activities. In addition, there is no practical system that can automatic detect emotions close to real life with high accuracy. In this paper, multimodality approach based on wireless EEG and ECG devices are used to detect emotional state. EEG and ECG signals of 8 subjects are acquired as they are watching videos and their effective state is presented. Remaining of the paper is organized as follows: Section 2 starts with data collection and explains about the experimental set up and participant self assessment. Data analysis is presented and section 3 and results are presented in section 4 and paper concluded in section 5 with conclusions and future directions.

Data Collection

We carried out an experiment with visual stimuli to collect affective EEG data and physiological ECG data.

Audio-video Stimuli

In research of emotion [2, 6, 34] several kinds of elicitation techniques are used. Whereas pictures stimulate the participants in a visual way, music is used for an auditive stimulation. According to literature [20, 31] the elicitation of emotion with video clips

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comprises a combination of both advantages and is used in this work.
Furthermore, it is important to know which emotion is elicited by which video. For this aim Gabert-Quillen et al. [23] investigated different video clips with different lengths. They cut out scenes from several movies and showed them to over 300 participants. At the end they created a database of 18 video clips where every clip is taken from a different movie. Their experiments proved that respectively, two of the clips are suitable to evoke one of nine different emotions. For that reason the whole dataset was split in two parts, where the total length of every part is almost the same.

The splitting of the set of video clips has several advantages. If the duration of the experiment is too long the subjects easily get tired or bored, which is an unwanted additional mental state. For example, if a person gets tired the power of the alpha band in the recorded EEG signal is increasing, whereas the power of the beta band is decreasing. Additionally Picard et al. [15] have shown that extracted features from signals which are recorded on different days under the same conditions can differ from each other. The reason for this daily dependency is that people can have different moods on different days. Furthermore, skin conductivity, hormone level and slight differences of electrode positions can affect the recorded signals [15].

Considering these facts the splitting of the set of video clips offers the opportunity to record signals from all the subjects on different days. Finally, it is possible to investigate these dependencies and opportunities to remove them from the signals [6, 19, 35].

Participants

In our first experiment we recorded eight different subjects aged from 23 to 30 (M = 26.8, SD = 2.1). To make results independent from genders we have recorded signals from both female and male participants.

Experimental Setup

The experiment was executed in an isolated room to prevent outside influences. An electrical curtain darkened the chamber completely. The videos were shown on a 45" monitor. For measuring the bio physiological signals, a sensor device of Shimmer [28, 38] and an Emotiv EPOC headset [33, 36] were used for ECG and EEG data acquisition respectively as shown in Figure 1.

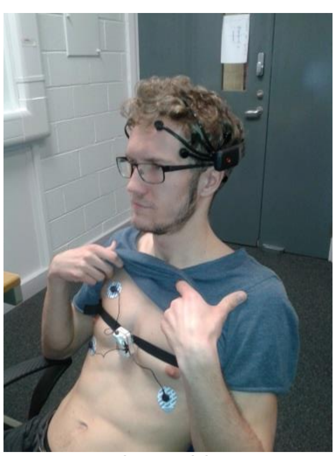

Figure 1: EEG and ECG data acquisition set up.

Experimental Protocol

After arriving the subjects asked to read an *Information Sheet* which provides further details about the procedure of the experiment. If a participant wants to participate he has to fill out and sign a *Consent Form*.

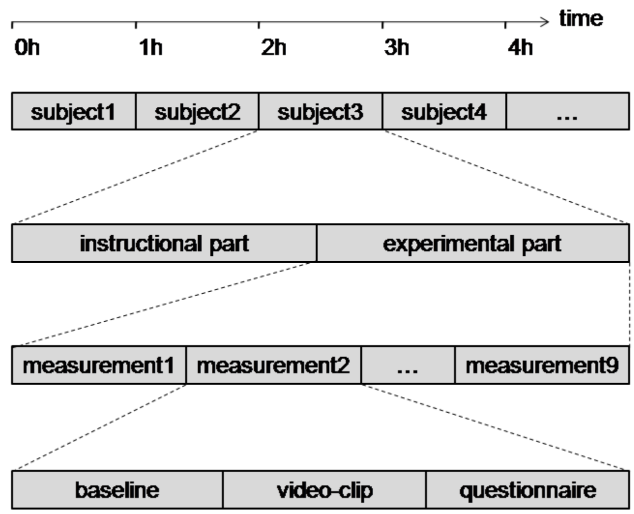

Figure 2: Schematic of experiment protocol

With around 30 minutes, the two different video assemblies have almost the same length. Koelstra et al. [6] and Wagner et al. [19] have shown that it is possible to remove daily dependencies using baseline signals. Therefore a baseline measurement is included before each clip is shown. The baseline signals are recorded whilst showing the introductory film clip provided by Gabert-Quillen et al. [23]. Furthermore the participants have to give response regarding their feelings during the video after an emotion eliciting clip was shown. The whole procedure of the experiment is shown in Figure 2

One whole session of the experiment lasts around one hour. Before each experiment starts the people were asked to keep sitting with as less as possible motions. Additionally the participants were also encouraged to rate what they truly felt and not what they think which emotion was intended to feel.

For the execution of the experiment a graphical user interface (GUI) is implemented in a Matlab environment as shown in Figure 2. This application controls the procedure of the experiment. At the beginning some information (like name, age and gender) of the subjects are taken. According to the aforementioned experimental protocol the baseline clip and film clips are played automatically. After that the GUI shows questionnaires so that the subject can give his ratings as shown in Figure 3. Finally the recorded data, the participant's choices in the questionnaire and the personal information are stored in a data structure.

Participant Self Assessment

After a clip is shown, the subjects have to fill out a self assessment. The manner of this questionnaire is orientated on the work of Gabert-Quillen et al. [23]. In this way it is possible to compare the ratings of the participants after they completed the

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second session of the experiment with the ratings of the over 300 subjects from Gabert-Quillen et al. [23]. Finally it is possible to evaluate the recorded data regarding their emotional content.

It is proven that self assessment manikins (SAM) are very suitable to label the levels of arousal, valence and dominance [22, 23]. In our case all participants have to distinguish the dimensions in five steps. After this rating is done the GUI shows another questionnaire. All in all 19 different emotional expressions are listed. Each expression has to be rated by the participant with a number from zero to eight. The number is value for matching of the according expression to the feeling the subject had during watching the last film clip. In this context the participant chooses eight when the word matches extremely to his mood whereas zero means that he felt it not at all.

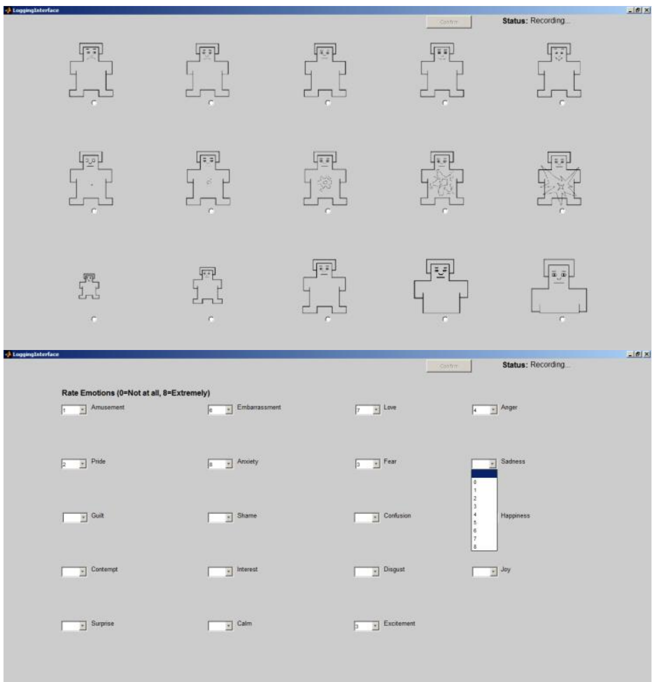

Figure 3: SAM questionnaire and Emotion rating GUI

Data analysis techniques

After retrieving the raw signals a first preprocessing was made to remove artefacts and transients. In the next step features are extracted out of the signals to train several classifiers. Finally a cross-validation algorithm is used to evaluate the quality of the classification.

For further calculations the second lead (RA-LL) of ECG signal is used. The Shimmer sensor device captures the signals with a sampling frequency of 256 Samples per second. We used a Butterworth band pass with 20^{th} order and cut off frequencies at 0.02 Hz and 40 Hz to remove the offset and high frequency transients. Totally 84 features (statistical, time-domain, frequency domain) are extracted out of the ECG signals using the *Augsburg Biosignal Toolbox (AuBT)* [21].

The Emotiv EPOC headset measures the EEG signals with 14 electrodes locating at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 [33] to record EEG data. The sampling rate is 128Hz. Due to non-phase-locked alpha waves within each trial frequency domain analysis is required to detect alpha activity reliably. To calculate bandpower it is not necessary to filter outbound frequencies. Nevertheless those unwanted frequencies of artefacts can affect signal processing using the signals in time domain. Eye artefacts and ECG interferences have their biggest influences mostly at frequencies below 5 Hz. In contrast the main frequencies of muscle artefacts can be found above 20 Hz. Therefore a Butterworth band pass in the range from 5 Hz to 20 Hz is used to remove most of those artefacts.

The emotional state of a person changes over time. For that reason we only used the second halves of each signal to extract features, to give the subject the opportunity to forge its emotional state during the first half. Afterwards every signal is split into five second segments. In this manner the amount of trials has been increased what is helpful for a better statistical validation. EEG features alpha and beta bandpowers are widely used in literature [16, 24, 34]. Welch's power spectral density (PSD) is used to calculate powers of the alpha band from 8 Hz to 12 Hz and a section of the beta band from 14 Hz to 18 Hz. Within every five second trial Fast Fourier Transformation (FFT) is calculated over a one second window for five times. After that the five retrieved values are averaged to one. Finally two band powers for each of the 14 electrodes can be used as features.

The feature vectors
$\omega ecg = [\omega ecg(1) \ldots \omega ecg(84)]$, and
$\omega eeg = [\omega eeg(1) \ldots \omega eeg(28)]$
are used to train each classifiers, namely LDA, NBC, KNN(k=10), Decision Tree, and SVM. We have chosen a small number of different types of supervised learning algorithms out of much more available classifiers evaluated by Fernández-Delgado et al. [14]. In their research Kreibig [17] and Murugappan et al. [20] used the Heart Rate Variability (HRV) which is calculated from the ECG signal to recognise excitement states. On the other hand it is proven that the activity of the left and right hemisphere of the brain is suitable to distinguish between negative and positive feelings [29, 34]. Therefore we decided to use the ECG features for classification of three arousal levels (low, middle and high) and EEG features for valence recognition (positive and negative). In the following the subject’s ratings for valence and arousal are separated to the according amount of classes. In the last step of recognition we used a 10-fold cross validation for the evaluation of the classification system. The data is split into ten groups of the same size. Then nine groups are used to train the classifiers and one group is used for testing. The whole procedure is executed ten times till every group was once used for testing.

Results

As aforementioned the quality of the recorded data can be evaluated by comparing the subject’s ratings with the work of Gabert-Quillen et al. [23]. Russell et al. [25] proposed that different valence and arousal levels can be shown in a two-dimensional diagram. All arousal and valence level ratings are averaged over the eight different subjects. The results of this procedure are shown in Figure 4.

It is obvious that some of the video clips are situated more closely to the result of Gabert-Quillen et al. [23] than others. For instance the scenes from *Remember the Titans* (valence close to

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4.5, arousal close to 3.5), *Pride & Prejudice* (valence close to 4, arousal close to 1.5), *The Gentlemen's Agreement* (valence close to 2, arousal close to 2.5), *The Departed* (valence close to 2.5, arousal close to 3.5) and *The Fly* (valence close to 1.5, arousal close to 4) show an almost perfect merging. Other film clips like *Searching for Bobby Fischer*, *The Bourne Identity*, *Modern Times*, *Dead or Alive*, *The Ring*, *The Hangover* and *Crash* merge the results of Gabert-Quillen et al. [23] good. Only a few video clips (*My Girl*, *The Shawshank Redemption*, *Wall-E*, *300*, *Psycho*, *National Lampoon's Van Wilder*) have not so good but are placed in the same region.

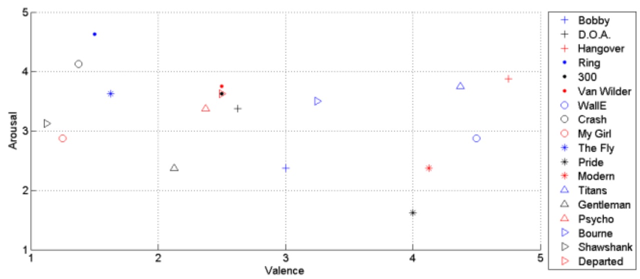

Figure 4: Averaged valence and arousal ratings of the subjects

Several types of single classifiers were used to categorise data of each subject separately. As described by Gibson et al. [27] each system was analysed by calculating true positive, true negative, false positive and false negative results. In case of valence classification, where two classes need to be distinguished, recall demonstrates how many negative valence ratings were correctly classified and specificity demonstrates correct classified results of positive valence. Whereas in case of arousal classification three classes need to be distinguished. Therefore specificity is replaced by recall for class 2 (middle arousal) and recall for class 3 (high arousal). In this context, we applied a meticulous model for SVMs since SVMs are usually not able to classify more than two classes.

Based on the ratings of one participant it is not possible to extract three arousal states due to only ratings of two out of three available arousal levels. Therefore, classification results of the seven remaining participants were averaged for every classification model separately and are shown in Tables 1-2.

Table 1: Valence classification results.

	LDA	NBC	KNN	TREE	SVM
Accuracy (%)	72.9	70.2	74.5	73.1	73.4
Recall (%)	85.3	75.5	83.3	78.0	88.2
Precision (%)	74.8	76.5	77.4	78.6	74.6
Specificity (%)	49.2	60.1	58.1	64.1	44.8
Average (%)	70.6	70.6	73.3	73.4	70.2

Table 2: Arousal classification results.

	LDA	NBC	KNN	TREE	SVM
Accuracy (%)	61.9	60.8	65.6	63.4	65.7
Recall cl.1 (%)	40.9	51.5	30.5	49.6	40.8
Precision cl.1 (%)	47.3	47.5	46.0	46.1	52.0
Recall cl.2 (%)	71.2	68.6	82.7	70.3	76.8
Precision cl.2 (%)	67.4	70.2	67.7	70.7	68.2
Recall cl.3 (%)	39.3	50.9	21.5	42.7	39.4
Precision cl.3 (%)	39.6	39.5	42.6	46.9	45.1
Average (%)	52.5	55.6	50.9	55.7	55.4

For valence classification all systems perform well in average within the range of 71-73%. Also the classification rate of arousal within the range of 51-56% for average is basically much higher than chance level for three classes. No single classifier performs notably much worse than the others. However it is obvious that recall results are higher than specificity within valence classification. This situation occurs due to a unequal distribution of ratings for both classes. More labels for class one were rated and the classifiers tend to perform better for the left hemisphere of the confusion matrix. A similar case can be noticed within arousal classification results. Classifiers perform best in detection of class two, where the most labels were rated and the classifiers apparently can fit the model better.

Conclusions

In our work we executed an experiment to capture ECG and EEG signals from four female and four male participants. During the experiment 18 scenes from movies were shown to induce different emotional feelings. After each clip subjects had to assess their feelings about the clip. For execution, we implemented a GUI in Matlab to run the experiment automatically. The manner of the questionnaire is oriented on the work of Gabert-Quillen et al. [23]. After doing the first part of data analysis we got similar results like the results published by Gabert-Quillen et al. [23]. Knowledge about the subjects' feelings during the signals were recorded gives us the opportunity to use this signals for classification.

In the first step of data processing, we preprocessed the two recorded physiological signals. Further on, all in all 84 ECG features and 28 EEG features were calculated. After that, the two feature vectors are used to train five different classifiers. EEG observations were used to train the classifiers for valence recognition and ECG observations were used for arousal recognition respectively. We achieved averaged results of 71.6% for valence classification and 54.0% for arousal classification.

The results presented here were gathered through first examinations on the signals. It is already planned to implement more analysis techniques. Daily dependencies of the subject's data can be removed using the baseline signals. Especially for EEG recognition it is possible to calculate more features similar to the features used for ECG recognition. Up to now every feature which was calculated is used in the classification. But there are several feature selection algorithms which can remove these ones which are not suitable. A kind of outlier detection can be used to find channels which recorded signals with less quality because of less conductivity of the electrode during the experiment or participant movements. Using this additional algorithms it is possible to improve the recognition accuracy and implement a system for HCI which is able to recognise different emotional states.

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