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Towards wireless emotional valence detection from EEG

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Abstract—**Intelligent affective computers can have many medical and non-medical applications. However today's affective computers are limited in scope by their transferability to other application environments or that they monitor only one aspect of physiological emotion expression. Here, the use of a wireless EEG system, which can be implemented in a body area network, is used to investigate the potential of monitoring emotional valence in EEG, for application in real-life situations. The results show 82% accuracy for automatic classification of positive, negative and neutral valence based on film clip viewing, using features containing information on both the frequency content of the EEG and how this changes over time.**

I. Introduction

Intelligent affective computers have many advantages in an increasingly technological society, both in medical and non-medical applications. However to know our emotions, we must be able to measure them. Multiple methods exist for measuring emotions, such as monitoring facial expressions, measuring emotional cues in speech, measuring physiological signals, and measuring cognitive activity [1]. While each of these methods has its own advantages, current technology limits the scope of emotion monitoring either to a single environment such as the car [2], sitting in front of a monitor/camera [3], or limited monitoring during normal daily activities [4], and all with limited success.

Body Area Network technologies provide the capabilities to measure the emotional state of the person based on their physiology, unobtrusively as they go about their everyday life, through miniaturized, wearable wireless sensors. These wireless sensors can be placed in multiple locations on the body, to be able to monitor multiple physiological parameters simultaneously.

Previous efforts [5], [6] have focused on detecting emotional state from peripheral physiological sensors with three classes, high arousal-negative, neutral arousal-positive, and low arousal-negative, being classified with 64% accuracy. Based on these results, a method was implemented that detects the subject's arousal level in real time [6]. While this device is sufficient for monitoring arousal, to fully understand the emotional status of the person, the valence of the emotion also needs to be determined.

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This paper focuses on using a wireless 8-channel EEG sensor to measure emotional valence in the brain, and investigating the potential of new features derived based on the dynamics of cognitive emotional processing [11], towards using hemispheric asymmetry for detecting emotional valence in real-life situations.

II. Emotions in EEG

Emotional arousal is said to correspond to the level of physiological activation in response to a stimulus, and the valence of the emotion is commonly attributed as the psychological appraisal given to the stimulus [7]. While multiple theories of the nature of emotional processing in the brain exist, electroencephalography (EEG) studies have shown that emotional processing in the brain can be detected from the asymmetry in the brain activity recorded by EEG. Two models for this asymmetry exist: the Right hemisphere hypothesis, which states that emotions are processed in the right hemisphere [8]; and the Valence hypothesis, which states that there is differential hemispheric specialization for positive and negative emotions. That is, the left hemisphere is dominant for processing positive emotions while the right hemisphere is dominant for processing negative emotions [8]. In addition, anatomical studies have shown that emotions are processed primarily in the pre-frontal cortex with high affect asymmetry, however that the asymmetry can vary due to varying underlying structures [8].

Using such asymmetry, automatic classification of emotion based on the peak alpha frequency, alpha power and cross correlation of alpha power between electrodes, has been reported to achieve accuracy of up to 66.7% for 3 classes of emotional pictures (negative, neutral and positive) for a single subject, with variations across 5 subjects of 48.89-66.67% [9]. In the same study, using only frequency domain information, the mean accuracy was 44%. Another study [10] using consonant and dissonant music, found no hemispheric lateralization due to the variation in emotional valence in the alpha bands analyzed, although did find an increase in the frontal midline theta power during the consonant music compared with the dissonant music.

III. Methods

A. Subjects

Eleven subjects (8 male, 3 female, mean age 33.4 years, range 26-44) participated. Ten subjects were right handed, one subject left handed.

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Clip 1: Baseline, Eyes open/Eyes closed	Clip 2: Neutral	Clip 3: Positive	Clip 4: Negative	Clip 5: Positive low arousal	Clip 6: Negative high arousal	Clip 7: Neutral	Clip 8: Positive high arousal	Clip 9: Negative low arousal
Baseline	Film Clips			Picture blocks				

Figure 1: Experimental Protocol

B. Stimuli

The stimuli used to elicit the emotion included both film clips and pictures selected from the IAPS database [12]. As the aim of the investigation is to detect emotional valence from EEG, three film clips were used corresponding to one clip for each of neutral, positive and negative valence. Film clips were selected to have similar arousal levels to ensure the measured effects were due to the emotional valence and not the arousal. The content of the film clips was guided by previous studies reported in literature [13]. The films ranged between 57 seconds and 230 seconds length.

Pictures from the IAPS database were chosen and grouped into 5 classes: positive-low arousal, positive-high arousal, negative-low arousal, negative-high arousal and neutral based on reported scores. For each class, a slideshow containing 8 pictures was shown, with each picture shown for 6 seconds, for a total of 48 seconds per class.

C. Physiological Measurement

EEG was measured using an ultra-low-power wireless 8-ch EEG sensor developed by imec [13]. Eight Ag/AgCl cup electrodes were attached to the scalp using conductive EEG paste after skin preparation so that all impedances were below 5 kOhms. EEG was measured from Fp1, Fp2, F3, F4, F7, F8, C3 and C4. Cz was used as reference electrode, while the right mastoid was used for the grounding electrode. Signals were sampled at 1024 Hz. The sensor contained hardware filters: high pass filter with cutoff 0.5 Hz, and low pass filter with pole 1 at 100 Hz and pole 2 at 210 Hz.

Skin conductance was measured using a wireless skin conductance sensor [5].

D. Experimental Protocol

Experiments took place in a closed laboratory, with the subject seated behind a partition wall separating the subject and the experimenter, allowing the experimenter to monitor the EEG data and the presentation stimuli to ensure the protocol ran smoothly.

The stimuli were shown on a 17-inch computer screen; however with the low resolution of the stimuli, the stimuli were shown at approximately 9-inches diagonal. The distance between the subject and the computer screen was approximately 2 feet, allowing good view of the stimuli. Headphones were used to deliver the sound during the film clips. Questionnaires were answered using a mouse, controlled by the right hand.

Before emotional stimuli was shown, baseline EEG was measured using 2 minutes resting with eyes open followed by 2 minutes resting with eyes closed.

First the film clips were shown, and then the 5 slideshows of emotional pictures were shown. Between each stimulus, subjects were asked to complete the self-report rating questionnaires. The stimuli program would only continue once all questionnaires were answered, so there was no fixed time to respond to the questionnaires. Between each questionnaire and the next picture slideshow, 15 seconds rest was given. The protocol was structured as shown in Fig. 1.

E. Feature Extraction

The computed features consist of features related to the ratio of alpha power in the left and right electrodes, and features related to the band powers in a given electrode.

Alpha power ratio features For each electrode pair, 3 features were calculated using the ratio of alpha power in the left and right electrodes. They are: maximum and kurtosis of the alpha power left/right ratio, and the number of peaks per minute in the alpha power left/right ratio. To calculate the alpha power left/right ratio, first the alpha profile during the clip was generated using Matlab's spectrogram method with window length of 2 seconds with zero overlap. For each time step, the power in the alpha band 8-12 Hz was then calculated. The ratio was then calculated as alpha left/alpha right for each time step. The result was a profile of the dynamics of the alpha left/right ratio over the period of the recording. The maximum and kurtosis of this ratio was then found for each stimuli clip. To calculate the number of peaks per minute in the alpha left/right ratio for each clip, a threshold was set at mean plus 2 standard deviations, and the number of peaks determined. To normalize over the length of the clips, the number of peaks was then divided by the length of the clip to give the total number of peaks per minute.

Band Power features As previous literature suggests that the entire alpha band is too large [10], the powers in 3 smaller frequency bands were calculated. The bands used were alpha1 (6-8 Hz), alpha2 (8-10 Hz), and alpha3 (10-12 Hz). Band powers were calculated by first band pass filtering the EEG signal with a 1000 order FIR filter with cutoff frequencies 5 and 35 Hz. Then the power spectral density was found using Welch's method with window length 4 seconds with 50% overlap. For each clip, the average power in each band was then calculated.

An additional feature, the peak alpha frequency was also determined from this power spectral density, as the peak alpha frequency is suggested to also vary with emotion [9].

These features were calculated for each electrode position, resulting in 44 features per clip per subject.

In addition to the EEG features, the second difference of the skin conductance signal, together with visual analysis of the questionnaire responses was used to determine if the emotion was induced.

F. Feature Selection

Prior to performing any analysis or classification, the feature set needed to be reduced significantly to avoid errors related to the curse of dimensionality. In the first instance, the electrode positions Fp1 and Fp2 were removed based on the presence of EOG artifact. Positions C3 and C4 were removed as emotional processing is reported to occur mostly over the frontal regions of the brain [8], thus C3 and C4 were seen as less relevant positions for this study and removed. The feature set was further reduced using statistical analysis and classification.

G. Statistical Analysis and Classification

Each feature was plotted and visually inspected using a boxplot for each stimuli clip to inspect variations across clips. Next, statistical analysis of each feature was performed using pair-wise t-test for film clip combinations to investigate if significant differences are observed in the features. Pattern classification techniques were then applied to estimate classification performance. It was decided to use several classifiers to see if results would generalize among the different classifiers. Here, quadratic discriminat classifier (QDC), support vector machine (SVM) and K-nearest neightbour (KNN) classifiers were used for comparison. First features were ranked based on their individual classification performance. From this the highest ranking features were used for further analysis. Pattern classification was applied to film clips only, pictures only, and combining the film clips and pictures in one dataset, all with 2 class and 3 class classifications. For 2 class classification, two class definitions are used: neutral versus positive versus negative; and neutral/positive versus negative.

IV. Results

A. Database

Nine subjects from the 11 recorded were used in the analysis. EEG data from one subject was incorrectly recorded, while data from another subject was not used as the recording software stopped and had to be restarted during the experiment.

As a reference measure to ensure emotion was induced, using the second difference of the skin conductance, clip 4 (negative film) was shown to be significantly different from clips 2, 3, 5 and 8 which were all positive or neutral film clips and pictures, while clip 4 was not significantly different from clips 1 (baseline) or clips 6 and 9 which were both negative pictures, with p = 0.007. Additionally, the questionnaire results were visually inspected, and emotional changes were reported in line with the findings from the skin conductance analysis.

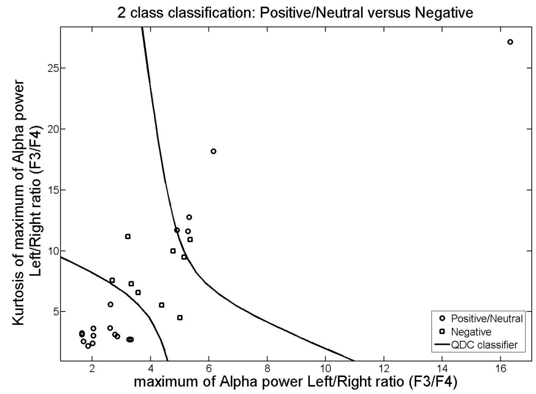

Fig. 2: scatter plot of 2 class classification using the maximum of alpha power left/right ratio at F3/F4 and the kurtosis of this maximum, with QDC classifier shown

B. Statistical Analysis and Classification

Applying t-test to the film clip combinations for all remaining features, over all features and clip combinations, significant difference was found for the maximum of the alpha power ratio for positions F3/F4 ($p=0.0094$) and the kurtosis of the maximum of alpha power ratio for position F3/F4 ($p = 0.008$) for the positive and negative film clips. Further feature selection was done using single-feature pattern classification using the film clips only, resulting in four features identified as having high classification importance. They are given in Table I.

Using the film clips only, Table II shows the classification rates for 2 and 3 class classification using QDC, SVM, and KNN. Fig. 2 shows the 2 class scatter with QDC classifier.

TABLE I
SINGLE FEATURE CLASSIFICATION FOR RANKING

Rank	Feature (F3/F4)	Classification
1	number of peaks per minute in the ratio of alpha power left/right	89%
2	the kurtosis of the maximum of the ratio of alpha power left/right	67%
3	maximum of the ratio of alpha power left/right	41%
4	power in band alpha2 (8-10 Hz) in electrode F4	30%

TABLE II
CLASSIFICATION RESULTS, USING FILMS ONLY WITH MULTIPLE CLASSIFIERS USING MAXIMUM AND KURTOSIS OF MAXIMUM OF ALPHA POWER LEFT/RIGHT

Number of Classes	Classifier	Classification	
		F3/F4	F7/F8
3	QDC	53%	52%
	SVM	44%	46%
	KNN	64%	50%
	KNN*	82%	81%
2 Positive and Neutral versus Negative	QDC	80%	78%
	SVM	61%	76%
	KNN	85%	70%
	KNN*	77%	85%

*using the number of peaks per minute in the ratio Alpha power Left/Right and the power in band alpha2 (8-10 Hz) in F4

Using the KNN classifier and the maximum and kurtosis of the maximum of the alpha power left/right, combining the film clips with the pictures in 3 classes, the accuracy is reduced to 48%. Using the pictures only, for 3 class classification the accuracy is 48% while for 5 class classification the accuracy is 26%.

V. Discussion

The results obtained show promising progress towards detecting emotional valence from EEG. The new features implemented show significant improvements in performance over the traditional frequency content features, and may provide additional insight into the brain dynamics and cognitive processes beyond what has previously been reported. In particular, little information is available on the how the frequency content and cerebral asymmetry changes over time during emotional processing, and the ability to use this to detect emotional valence from EEG. These results suggest that emotional information is related not only to hemispheric asymmetry, but needs to be captured on a short time-scale to allow the emotional evaluation to occur but to prevent information lost to averaging over the stimuli period.

Using the pictures only resulted in 41% classification accuracy for 3 classes, similar to previous literature [9]. This is much lower than the 82% classification accuracy when using only the film clips. This suggests a large difference in the cognitive responses to the pictures compared with the film clips, which needs further investigation as the data set presented is limited. Additionally, to properly evaluate the ability to detect emotional valence from EEG during daily activities, further work is needed where the stimuli is based on daily activities rather than film clips or pictures.

VI. Conclusion

During film clip viewing, the emotional valence can be detected with 82% accuracy for 3 classes: positive, negative and neutral. The features that gave the highest classification results were not only related to hemispheric asymmetry, but also the dynamics of the activity. When combined with a wireless EEG sensor, these results show the potential for wireless emotional valence detection from EEG, with the potential for real-life applications.

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