Emotion Classification Using Single-Channel Scalp-EEG Recording

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Abstract— **Several studies have found evidence for corticolimbic Theta electroencephalographic (EEG) oscillation in the neural processing of visual stimuli perceived as fear or threatening scene. Recent studies showed that neural oscillations' patterns in Theta, Alpha, Beta and Gamma sub-bands play a main role in brain's emotional processing. The main goal of this study is to classify two different emotional states by means of EEG data recorded through a single-electrode EEG headset. Nineteen young subjects participated in an EEG experiment while watching a video clip that evoked three emotional states: neutral, relaxation and scary. Following each video clip, participants were asked to report on their subjective affect by giving a score between 0 to 10. First, recorded EEG data were preprocessed by stationary wavelet transform (SWT) based denoising to remove artifacts. Afterward, the distribution of power in time-frequency space was obtained using short-time Fourier transform (STFT) and then, the mean value of energy was calculated for each EEG sub-band. Finally, 46 features, as the mean energy of frequency bands between 4 and 50 Hz, containing 689 instances—for each subject —were collected in order to classify the emotional states. Our experimental results show that EEG dynamics induced by horror and relaxing movies can be classified with average classification rate of 92% using support vector machine (SVM) classifier. We also compared the performance of SVM to K-nearest neighbors (K-NN). The results show that K-NN achieves a better classification rate by 94% accuracy. The findings of this work are expected to pave the way to a new horizon in neuroscience by proving the point that only single-channel EEG data carry enough information for emotion classification.**

I. INTRODUCTION

Emotions play an undeniable role in human-human communication and in his survival. Considering the tightly coupled role that machines and computers play in our commonness, recently, emotional interaction between machines and humans has turned itself as an interesting area in brain computer interface (BCI) [1]. Numerous studies, particularly with two major inclinations have been conducted for emotion recognition: studies in which the main goal is surveying the facial expressions [2] ,[3], and the other group of investigations which study the changes happen in different brain areas while experiencing emotional states, using the captured signals from the central nervous system such as electroencephalography (EEG), electrocorticography (ECoG), and functional magnetic resonance imaging (fMRI). Among these signals, EEG has been proved to provide informative characteristics in responses to the emotional states [4], [5].

Davidson et al. [6] suggested that the frontal brain electrical activity appears to be responsible for emotional response. Coan et al. [5] suggested that EEG asymmetry serves as (1) an individual difference variable related to emotional response and emotional disorders, and (2) a state-dependent concomitant of emotional response. They suggested that frontal EEG asymmetry may serve as both moderator and mediator of emotions. These findings encouraged a variety of other science areas such as signal processing, machine learning and human-computer interaction to investigate EEG-based emotion recognition[7], [8].

Such investigations focus on two areas: surveying the electroencephalographic dynamics through different emotional experiences [6], [9], and processing or classification of recorded EEG data during each emotional state [10].

In terms of tracking EEG dynamics during distinct emotional states, various emotions such as fear, sadness, happiness, disgust, anger, joy, and relaxation were surveyed. In some studies, emotions were categorized in two general groups: (1) negative (e.g. sadness, disgust, anger, fear); (2) positive emotions (e.g. joy, happiness, relaxation) [11], [12] and [13]. Among these emotions, fear and relaxation were considered in some recent studies [9], [14] and [15].

Relaxation refers to a physical state of deep rest, physiologically defined as a decrease in sympathetic activity (decreased heart and respiratory rate, blood pressure, oxygen consumption and reduction in cortisol and noradrenaline) [15]. Friedman et al. [16] conducted a controlled and randomized study about the central nervous system effects of relaxation techniques (RT), using spectral analysis of EEG activity. They reported increased Theta activity during the practice of RT. In a study conducted by Dunn et al. [17] a decreased Theta power over the entire scalp during two different meditation practices called Shamatha and Vipassana, was reported.

Fear, on the other hand, is an intense reaction to an external or internal threatening stimuli and has a direct relationship with anxiety state [18]. In human, fear response is mediated through the limbic system, which includes phylogenetically ancient pathways [19]. For threatening and fearful experiences, an increased Theta activity in frontal and prefrontal cortex was reported [14], [9]. DeLaRosa et al. [9] found differential topographical Theta power changes as a function of time. They also observed a consistent left

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lateralized Beta desynchronization, in response to threatening images.

For having emotional interaction with computers, emotions should be recognized with a high accuracy through a robust system against artifacts. To this end, several studies focused on classifying EEG bands for different emotions. Iacoviello et al. [10] conducted a research to make a real-time classification algorithm for EEG-based system driven by self-induced emotions. Their experiment involves showing a group of symbols to subjects and asking them to concentrate on different emotions such as disgust, fear, anger and hunger and consequently an average classification rate of 90% using support vector machine (SVM) was obtained. Wang et al. [20] designed a movie induction experiment that spontaneously led subjects to have real emotional states. After watching movie, they used a self-assessment manikin (SAM) to verify EEG-based emotion classification and in the end, they collected an EEG data set of six subjects and reported the classification accuracy of 87.53% using SVM with linear kernel. Jirayucharoensak et al. [21] implemented an EEG-based emotion recognition system using a deep learning network. They applied the principal component analysis (PCA) to extract the most important components of initial input features in order to alleviate the over-fitting problem and they managed to classify valence and arousal with accuracies of 46.03% and 49.52%, respectively. Furthermore, they implemented the covariate shift adaptation (CSA) of the principal components to minimize the non-stationary effect of EEG signals. They reported that using CSA enhanced the classification rates for valence and arousal by 5.55% and 6.53%, respectively. Mu et al. [22] used a 62-channel electrode cap for classifying two emotions —happiness and sadness —evoked by showing subjects some pictures of smile and cry facial expressions, using SVM. They achieved classification accuracies of 93.5% $\pm$ 6.7% and 93.0% $\pm$ 6.2% on 10 subjects for 3s-trials and 1s-trials, respectively. They also reported that Gamma band is suitable for EEG-based emotion classification. Jatupaiboon et al. [23] used SVM for classifying negative and positive emotions elicited by pictures and they could classify the EEG features with 85.41% accuracy. They also mentioned that frontal pairs of channels yield better results in comparison with other areas. Zheng et al. [24] used a deep belief network (DBN) to classify two emotional states (positive and negative) using EEG data obtained from a multichannel EEG equipment. Their method achieved 87.62% classification accuracy.

In this paper, we intend to recognize fear and relaxation through movie screening, using just one dry electrode—as a low-cost solution—, placed over left frontal cortex and then to classify EEG dynamics related to fear and relaxation with an acceptable accuracy. In addition, we propose to use stationary wavelet transform (SWT) based artifact removal algorithm for improving the classification rate in emotion classification task.

The rest of this paper is organized as follows: Section II describes the methods and materials (including the characteristics of participants, stimuli, data acquisition, EEG preprocessing, EEG processing and feature extraction) used in this paper. In Section III, the experimental results are presented. It is followed by the conclusion in Section IV.

II. Materials and Methods

A. Participants and environmental settings

Nineteen healthy, right-handed adults between the ages of 19-32 years old (14 males, 5 females) participated in this study. All the principles outlined in the Helsinki Declaration of 1975, as revised in 2000 [25], have been followed in all the experiments involving human subjects during the current study. None of the subjects reported any neurological or physical impairment. The data from 11 subjects were excluded because of excessive noise or major movement artifacts —like touching either forehead, EEG equipment (6 subjects)—or because the subject reported that he had already watched the movies and he didn't experiment the fear emotion at all (5 subjects). Before starting the experiment, all the participants were asked to sit still. Also, no technical information was given to the participants about the experiment. This is different from some other investigations in which either participants have had some detailed information about experiment or they have been asked to focus on each corresponding emotion to a picture or movie clip, or the feeding behaviors had been controlled 24 hours before data acquisition [26], [12]. Our final cohort comprised 8 subjects (6 males and 2 females). The experiment was carried out in a dark small room using an LCD monitor and subjects sat 50 cm far from monitor. The room was devoid of any noise or interruption. After finishing the experiment, subjects evaluated their level of fear for horror movie and their general relaxation state during the relaxing movie, by giving a score between number 0-10 where score 0 indicates no fear at all and score 10 indicates most fearful state.

B. Stimuli

Gathering good and meaningful data is essential in any signal processing application. Due to the cognitive dependence of physiological signals —which requires the emotional states to be elicited internally in participants [27], acquiring data that correspond to a specific emotional state is challenging. To stimulate subject's fear and relaxation emotional states, a set of joint movie clips with a duration of 288 seconds were shown to the participants. There was no break time during the experiment. Previous studies have also used video clips as emotional stimuli [28], [29] and [30].

As shown in Table.I, the movie clip set consists of 2 movies which elicit two target emotional states: positive (relaxation) and negative (fear). The selection criteria for movie clips are as follows: (a) the movie has to be understood without explanation; and (b) both relaxing and horror movies ought to elicit single desired target emotion of subjects.

TABLE I

DESCRIPTION OF THE MOVIE CLIPS

Number	Film title	Target emotion	Year
1	The Elavator	Neutral	2011
2	Matra	Positive (Relaxation)	2012
3	Lights out	Negative (Fear)	2013

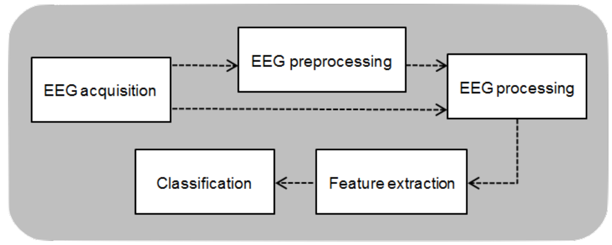

Fig. 2. The flowchart of emotion classification

TABLE II

FREQUENCY BANDS AND THE CORRESPONDING LABELS IN TRAINING DATASET.

SWT Coef. (Level = 6, Fs = 512 Hz)	d1	d2	d3	d4	d5	d6	a6
Freq. Band (Hz)	128 – 256	64 – 128	32 – 64	16 – 32	8 – 16	4 – 8	0 – 4
EEG Rhythm Component			Gamma	Beta	Alpha	Theta	Delta
Features for Training			F30 – F50	F13 – F30	F8 – F12	F4 – F7	
			The mean energy for time segmentation of 0.2 sec				

Before starting the data acquisition process, we arranged several experimental setups in order to find the best situation for obtaining the best possible data. Through these experiments, we found out that during the first minute of test, users tend to have some movements, such as trying to touch the EEG device and strong head movements that cause major artifacts. In order to avoid this phase, we decided to use a neutral movie during the first 90 seconds, which neither arouses negative nor positive emotion. Based on our experiment, this solution decreased the initial artifacts for the majority of subjects. The neutral movie is followed by relaxing (60 seconds) and horror movies (138 seconds). The process of our experiment is depicted in Fig.1.

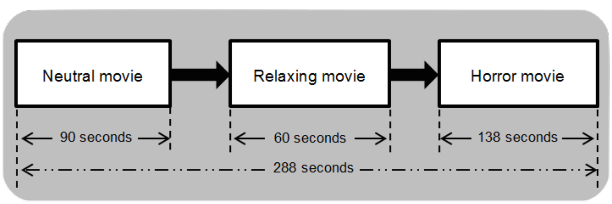

Fig. 1. The process of movie screening

C. EEG recording

One of the biggest challenges in EEG-related experiments is that EEG equipments are intrusive and hard to setup. This problem can be solved by using wireless or Bluetooth EEG headsets [31]. A wireless EEG headset (NeuroSky) with a single dry-sensor electrode attached to the forehead at position Fp1, a reference electrode on the ear clip, having a sampling rate of 512 Hz was used to record EEG data.

D. Methods

The recorded data were analyzed through several procedures including feature smoothing, signal processing, feature extraction, classification (Fig.2). One of the goals of the current study is to evaluate the effectiveness of the artifact removal algorithm. To this end, two kinds of training data were provided: (1) artifactual and (2) artifact-free.

E. EEG preprocessing

Stationary wavelet transform (SWT) based denoising (i.e. artifact removal) was chosen for its advantage over discrete wavelet transform (DWT) due to being translational invariant (e.g. small shift in signal doesn't cause significant changes in wavelet coefficients and large variations in distribution of energy in different wavelet scales) [32]. As a result, during denoising or signal reconstruction, no distortion in signal occurs [33], [34]. EEG data were preprocessed using scripts developed by the members of our laboratory, running under Matlab 8.3 (The MathWorks, Inc.). The preprocessing consisted of correcting the stereotyped artifacts including eye blinks, lateral eye movements, muscle and motion artifacts, using stationary wavelet transform (SWT) based denoising. 6-level decomposition of SWT with Haar, as basis wavelet (aka mother wavelet), has been applied on the recorded signal. After applying SWT, the output is a set of details (d1-d6) and final approximate coefficients (a6), representing distinct frequency bands of high and low frequency values, respectively, as shown in Table.II.

The modified universal threshold [35] was applied on different levels of wavelet coefficients to separate artifacts from EEG signal. Threshold value and threshold function are chosen according to the study carried out by Islam et al. [36].

The equations for threshold value calculation and garrote threshold function [46] are given below:

$$T_i' = K\sigma_i\sqrt{2ln(N)}; \tag{1}$$

where T_i' threshold value at level i. N is the length of data, σ_i is the estimated noise variance for W_i which is the wavelet coefficients at the i_{th} decomposition level ($W_i = a_i$ for approximation coefficient and $W_i = d_i$ for detail coefficients)

Threshold function, $\delta_i = \begin{cases} x; & |x| \leq T'_i \\ {T'}_i^2/x; & |x| > T'_i \end{cases}$

Where δ_i is the garrote threshold function at each decomposition level of i and the signal value of the wavelet coefficients, x. During denoising, we have carefully chosen the threshold parameter K to preserve desired signal of interest [36]. This is because the distinct frequency bands represent different EEG rhythms and some coefficients are more likely to contain artifacts where others very likely to contain desired signal. Finally, the artifact-reduced EEG sequence is reconstructed using the new set of wavelet coefficients by applying inverse SWT. The complete process flow of artifact removal is shown in Fig.3.

Fig. 3. Artifact removal process flow

F. Signal processing and feature extraction

Brain sub-bands consisting of *Theta* (4–8 Hz), *Alpha* (8–12 Hz), *Beta* (12–30 Hz) and *Gamma* (30–50 Hz), related to relaxing and horror movies, were decomposed using short-time Fourier transform. Using STFT, short pieces of signal with window function are extracted and then its frequency representation is computed:

$$F_x(t,f;h) = \int_{-\infty}^{+\infty} x(u)h^*(u-t)e^{-i2\pi uf}du \qquad (2)$$

where *h(t)* is the sliding analysis window of *STFT*. If the window has a finite energy then, it can be represented as:

$$x(t) = \frac{1}{E_h}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} F_x(u,f;h)h(t-u)e^{i2\pi tf}dudf \quad (3)$$

Where

$$E_h = \int_{-\infty}^{+\infty} |h(t)|^2 dt \qquad (4)$$

Afterward, each input time-series was divided into a sequence of discrete segments of 0.2 second and then, the mean energy was calculated for each frequency band during each of the time-segments. The self-reported forms were used to exclude data related to the parts of horror movie that didn't carry any fear emotion (e.g. closing credits). Finally, 46 features (F4, F5, ..., F50), as the mean energy of frequency bands between 4 and 50 Hz during each time-segment, containing 689 instances (388 instances for scary movie and 301 instances for relaxing movie) for each subject, labeled with either 'Scary' or 'Relaxing', formed two training datasets (artifact-free and artifactual).

III. Results

SVM with Pearson VII function-based universal kernel [37] and the cost parameter $C : C\epsilon\{10^{-5}, 10^{-4}, ..., 10^{2}\}$ was used for classifying different emotions. The train and test sets were randomly chosen from selected features, 70% and 30% from them respectively. As it is seen in Table.III and Table.IV, the average classification rate is increased (+3%) after using SWT based artifact removal. Although for subject #5 there is a -2.3% decrease and for subject #1 the results are same, but we can see an increase in classification accuracy between +1.4% and +8.4% for other subjects.

In order to find the best power spectrum feature for emotion classification, for both datasets, once the classification was done for each sub-band separately and then a combination of all sub-bands were used for classifying data. The best accuracy was obtained when a combination of all power spectrum features were engaged in emotion classification. Furthermore, the worst and the best average classification accuracies —considering independent sub-band —was obtained by Theta and Gamma bands, respectively. This finding is consistent with the result of the other studies in which it was mentioned that high frequency bands have a major role in emotional activities [20], [22]. In order to support the effectiveness of method, we repeated the classification for both datasets using K-nearest neighbors (K-NN). For $k = 2$, we achieved 94.1% and 90.2% average classification accuracy for artifact-free and artifactual datasets, respectively. The results obtained using K-NN show that applying SWT increased the classification rate by +3.9%.

TABLE III
CLASSIFICATION ACCURACY ACROSS DIFFERENT FREQUENCY BANDS USING SVM AND PEARSON VII FUNCTION-BASED UNIVERSAL KERNEL FOR ARTIFACTUAL DATA

Subject	Theta	Alpha	Beta	Gamma	All
1	58.4%	60.8%	67.1%	79.1%	91.1%
2	64.5%	63.8%	77%	83%	88.3%
3	59.6%	63.1%	77.2%	81.1%	90.8%
4	63.2%	62.6%	82.5 %	85.1%	94.1%
5	65%	60%	67%	58.3%	80.9%
6	58.5%	59.9%	88.3%	87.4%	94.1%
7	64.8%	70.1%	72.8%	69.8%	84.6%
8	56.1%	61.5%	70.5%	82.8%	88.3%
Average:	**61.3%**	**62.7%**	**75.3%**	**78.3%**	**89%**

TABLE IV
CLASSIFICATION ACCURACY ACROSS DIFFERENT FREQUENCY BANDS USING SVM AND PEARSON VII FUNCTION-BASED UNIVERSAL KERNEL FOR ARTIFACT-FREE DATA

Subject	Theta	Alpha	Beta	Gamma	All
1	57.6%	57.9%	75.7%	84.6%	91.1%
2	61.8%	60.2%	86%	84	96.8%
3	57%	64.2%	82.1%	89.5%	96.5%
4	64.2%	59.7%	60.6 %	87.9%	96.5%
5	65.3%	58.7%	66.4%	66.1%	78.6%
6	59.3%	62.3%	88.3%	87.4%	98%
7	75.7%	76%	83.7%	70.6%	89.4%
8	57.3%	59.7%	70.5%	86.7%	89.8%
Average:	**62.3%**	**63.3%**	**76.8%**	**82.1%**	**92.1%**

IV. Conclusion

In this paper, we investigated the characteristic of EEG dynamics for classification between relaxation and fear emotions using single-channel EEG recordings and we achieved an average accuracy of 92% and 94% using SVM and K-NN, respectively. It is found that the use of SWT-based artifact removal method has increased the average classification rate by 3%. Also, to find the best EEG feature for classifying fear and relaxation, we compared the classification results for power spectrum of differential asymmetry features and the best results were obtained using Gamma band, however, we had even a better result by using the combination of all EEG frequency bands between 4 to 50 Hz. The future development of this research will be focused on carrying out this experiment with more participants and more trials. Also, we would like to use other classification algorithms and to compare the results with those results obtained by SVM and K-NN, so as to find the most adequate classifier in similar study.

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