Emotion Recognition of Serious Game Players Using a Simple Brain Computer Interface

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***Abstract*—Understanding player's cognitive state and emotional response is necessary to make serious games more challenging and enhance the quality of human-machine interaction and gaming experience. Previous emotion recognition using brain computer interfaces (BCIs) is either relying a large number of wet electrodes or combining both brain signals with other peripheral physiological signals. In this paper, we investigate whether a simple BCI with only a few electrodes can identify basic or complex emotions in more natural settings like playing a game. We performed an experiment with 42 participants, who played a brain-controlled video game wearing a single electrode BCI headset and provided a self-assessed valence/arousal feedback at the end of each trial. By analyzing the data obtained from the self-evaluated questionnaires and the attention and meditation recordings from the BCI device, we introduce an automatic emotion recognition method that classifies four emotional states with the average recognition accuracy 66.04%.**

***Keywords*—emotion recognition; brain computer interfaces; serious game; NeuroSky**

I. Introduction

The use of serious games in training, education, health care, defense, and marketing is a way to increase the motivation in learning and decision-making process [1]. However, the risk that the players can get bored still exists. Understanding the player's cognitive state and emotional response is therefore necessary to make games more challenging and enhance the quality of human-machine interaction and gameplay experience.

Emotion assessment is often carried out through analysis of users' verbal and nonverbal behavior that communicates emotion [2]–[5], physiological signals [6], [7], or both [8], [9]. Due to the advances in biosensor, physiological signals, such as electroencephalogram, electromyogram, electrocardiogram, skin conductivity, and respiration change, are increasingly employed for automatic emotion recognition besides the conventional audiovisual emotion channels.

A Brain Computer Interface (BCI) is a direct communication pathway between the brain and an external device and electroencephalography (EEG) is the most practical non-invasive BCI capturing the brain signals in fine temporal resolution. The early BCI devices have been designed for clinical and research purposes partly due to their size and complexity [10]. In recent years, easy-to-use EEG-based BCI headsets such as the Emotiv EPOC, the NeuroSky MindWave, and the MyndPlay BrainBand have appeared to the game and entertainment market. Although such *simple* BCIs provide much coarser picture of brain activity than multi-electrode EEG, they often offer derived measures such attention and meditation levels as well as raw brainwaves, allowing easier data analysis and use in various applications including serious games.

Several studies have already demonstrated the usability of such commercially available simple BCIs as a means for obtaining user input or studying user's responses to stimuli. Rebolledo-Mendez et. al. [10] evaluated the usability of attention readings measured by NeuroSky's MindBuilder-EM, a low-cost, single dry electrode BCI and demonstrated the positive correlation between the measured attention values with user-reported ones. Patsis et. al. [1] exploited the attention levels obtained from NeuroSky's MindWave, a similar lightweight and inexpensive EEG-based BCI in order to adjust the difficulty of an educational video game according to the player's response. Crowley et. al. [11] used a simple BCI with three dry electrodes to monitor two mental states (i.e., meditation and attention) of individuals while performing a well-recognized psychological examination and showed the consistency between the stress level derived from the measured meditation readings and the observed stress evaluated by human experts.

Although previous studies have demonstrated the reliability and suitability of simple BCI as a tool for sensing brain activity and determining attention and meditation level, it is still unclear whether the EEG-based BCIs with only a few electrodes can measure basic or complex emotions in more natural settings like playing a game. Results reported so far on the EEG-based emotion recognition are either relying a large number of wet electrodes [12], [13] or combining both EEG signals with other peripheral physiological signals [8].

In this paper, we are investigating whether game player's emotional states can be identified using a simple BCI device. We perform an experiment with 42 participants, who play a brain-controlled video game wearing a single electrode BCI headset and provide a self-assessed valence/arousal feedback at the end of each trial. The subjective ratings obtained from the 42 players are analyzed to determine the target emotional

(a) Screen snapshot of Brain Pop game

(b) View of participant playing the Brain Pop game

Fig. 1. Brain-controlled video game used for the experiment

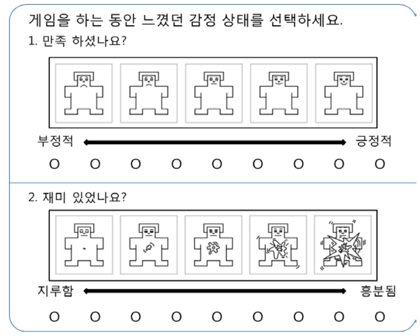

Fig. 2. The SAM used to rate the valence and arousal scores

states and to provide the ground truth for the automatic emotion recognition. The problem of emotion recognition can be considered as a multi-class classification, where a single binary classifier is trained per class to distinguish that emotional state from all other emotional states. Emotion recognition is then performed by applying the learned binary classifiers to an unseen sample and choosing the prediction with the highest confidence score. In our study, we decide to use the Naïve Bayes for the binary classifier per each emotional state since it provides the posterior class probability for the straightforward integration of the multiple binary classifiers. By analyzing the attention and meditation measures directly obtained from the BCI device with our emotion recognition method, we achieve the average recognition accuracy 66.04%.

The remaining sections of this paper are organized as follows. Section II presents the experimental setup and data acquisition, Section III introduces the simple BCI-based emotion recognition method, and Section IV concludes the paper.

II. Data Acquisition

In this section, we outlined the experimental setup including the brain-controlled video game used for the experiments and data acquisition including participants' self-assessment on their emotional response.

A. Brain-controlled Video Game

A brain-controlled video game developed at the Dongshin University Digital Contents Research Center (DU-DCRC) was selected for our experiment. This serious game, called Brain Pop, targeted at mind training and required the participant to focus and retain the concentration to increase the speed of the played music. Figure 1(a) shows the screen snapshot of the developed game. Brain pop was designed in that the better the player's ability to focus, the faster the selected music played. More specifically, the speed of the music in play was gradually changed in a range from 0.8 to 1.2 times faster than the original speed according to the accumulated attention level. Each player wore the NeuroSky MindWave headset[1] to interact with the game and the attention level directly obtained from the simple BCI device was used to control the speed of music in play. The video game was programmed using C++ and DirectX.

B. Experimental Setup

In our study, we used the NeuroSky's MindWave, a wireless BCI headset that has a single dry electrode placed on the forehead and captures EEG signal from the brain. This simple BCI and supported SDK provide information on user's delta, theta, alpha, beta, and gamma frequency band power as well as attention and meditation levels, a number per second in a scale from 0 to 100 for each cognitive state. The attention level was used as an input to the brain-controlled video game in order to control the speed of music in play.

Forty-two individuals (31 male and 11 female), aged between 20 and 75 (mean age 30.8), participated in the experiment. All participants played the brain-controlled Brain Pop game wearing the simple BCI device as shown in Figure 1(b). Each participant provided the demographic information such as age and gender to log into the game and then selected one song from the song list. Each participant was instructed to focus and maintain the concentration to make the chosen song played faster and finish the mind control game as early as possible. The attention and meditation recordings obtained form the BCI during each trial were logged in a file for further analysis.

C. Participant Self-Assessment

At the end of each trial, participants were asked to fill in a paper-based self-evaluation form giving scores for their

[1] http://www.neurosky.com/Products/MindWave.aspx

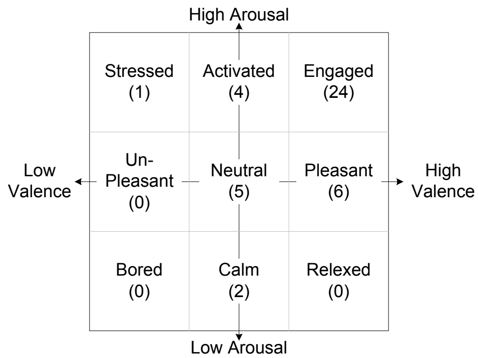

Fig. 3. Valence/Arousal 2D emotional plane with emotional feedback

valence and arousal feedback according to the 9-point Self-Assessment Manikin (SAM) as shown in Figure 2. The SAM is picture-oriented instrument devised to directly assess the valence (pleasure) and arousal associated in response to an object or event [14]. For valence, participants were instructed to give a lower score if they felt negative or unpleasant with their performance and overall gaming experience and a higher score if they felt positive or pleasant. For arousal, they were asked to give a lower score if they felt calm or bored and a higher score if they felt activated or excited with their performance. In our analysis, we used the self-assessed emotional feedback as the ground truth for the automated emotion recognition

III. Simple BCI-based Emotion Recognition

A. Analysis of Subjective Ratings

The subjective ratings obtained from the 42 players were first analyzed to provide the ground truth for the automatic emotion recognition using the simple BCI recordings, i.e., attention and meditation measures in our study. First, the 2-dimensional plane of valence and arousal was equally partitioned into 9 divisions, each representing a different emotion found in a gaming experience. According to the combination of valence and arousal scores, each trial was mapped to one of the nine emotional states. For example, a player who gave the valence and arousal scores, both ranging from 1 to 3 for his/her gaming experience, was considered to feel *bored* while playing the Brain Pop game.

Figure 3 shows the valence/arousal plane partitioned into nine emotional states and the results of the emotional feedback of all 42 players, where the number inside the parenthesis represents the number of players (trials) mapped to the corresponding emotional state. We could observe that 80.95% of the players felt *positive* emotions such as activated, engaged, and pleasant while only 7.14% of them felt *negative* emotions such as stressed and calm. Since we end up with few trials for some emotional states, the emotion recognition was conducted over only four emotions (activated, engaged, pleasant, and neutral) with more than three trials. As a result, only 39 trials out of 42 were retained for further analysis.

B. Emotion Recognition Method

The problem of emotion recognition can be considered as a multi-class classification, where a single binary classifier is trained per class to distinguish that emotional state from all other emotional states. Emotion recognition is then performed by applying the learned binary classifiers to an unseen sample and choosing the prediction with the highest confidence score. In our study, we decided to use the Naïve Bayes for the binary classifier per each emotional state since it provides the class probability as an output directly applicable for the confidence score of prediction.

Each of 39 trials initially represented as a sequence of attention and meditation measures sampled at 1Hz was first segmented with a sliding window of size 20s and 10s overlap, which results in 290 frames. Then, the sequence of attention and meditation measures within each frame was transformed into a feature vector. In specific, the mean, standard deviation, maximum, minimum, and slope information was individually extracted from the corresponding attention and meditation sequences to form a 10-dimensional feature vector. After the feature extraction, we obtained a *labeled* 290×10-dimensional data matrix and further processed this feature matrix with principal component analysis to get an uncorrelated data matrix for the subsequent four-class classification. For each emotional state, we trained a Bayesian classifier in the one-vs.-rest fashion, i.e., taking the feature vectors of that emotional state as a positive input and the remaining feature vectors of other emotional states as a negative input. At last, the final emotion recognition was determined by combining the posterior probabilities of the trained four classifiers. Figure 4 shows the overview of our emotion recognition using the readily available attention and meditation recordings from a simple BCI as an input and four Bayesian classifiers.

C. Results

In order to evaluate the performance of our emotion recognition method, we employed 10-fold cross-validation. The data set consisting of 290 feature vectors was randomly partitioned into 10 disjoint subsets (folds), where the data sample ratio among four emotional states was still maintained. Then, nine folds were used to train the four classifiers and the remaining one fold was to evaluate the trained classifiers. This process was repeated 10 times, leaving one different fold for evaluation each time.

Table I shows the confusion matrix of the emotion recognition based on a simple BCI recordings, where the last row is the average recognition accuracy. The most recognized emotions were engaged (69.59%) and neutral (64%). Activated was misclassified with neutral (50%) in the same mid-valence segment, while pleasant was misclassified with engaged (36.67%), an emotion also in the same high-valence segment. This implies that attention and meditation measures directly obtained from a simple BCI headset can distinguish emotions along the valence dimension better than the ones along the arousal dimension.

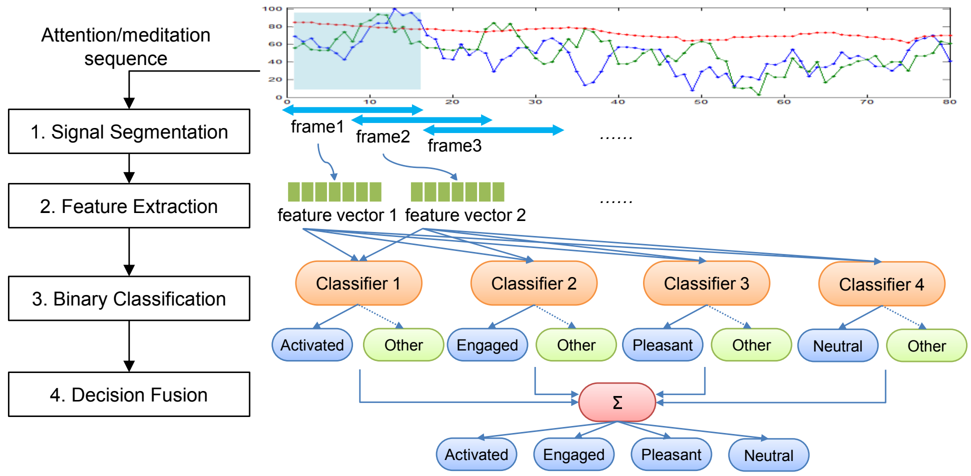

Fig. 4. Overview of emotion recognition method

TABLE I
RESULTS OF EMOTION RECOGNITION

	Activated	Engaged	Pleasant	Neutral
Activated	**37.50**	12.50	0.00	50.00
Engaged	0.52	**69.59**	9.28	20.62
Pleasant	0.00	36.67	**53.34**	10.00
Neutral	6.00	22.00	8.00	**64.00**
Average Accuracy	66.04%			

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we investigated whether a simple BCI with only a few electrodes could identify basic or complex emotions in more natural settings like playing a game. We performed an experiment with 42 participants, who played a brain-controlled video game wearing a single electrode BCI headset and provided a self-assessed valence/arousal feedback at the end of each trial. By analyzing the data obtained from the self-evaluated questionnaires and the attention and meditation recordings from the BCI device, we introduced an automatic emotion recognition method that classifies four emotional states with the average accuracy 66.04%.

As results of this preliminary study using the simple BCI for automatic emotion recognition were encouraging, we will repeat this experiment using a larger number of players and more trials per player to ensure sufficient trials for all nine emotional states and to demonstrate a stronger proof that simple BCIs are suitable and reliable means for emotion assessment. In addition, we will compare our recognition method with other emotion recognition approaches using artificial neural networks or support vector machines in terms of both effectiveness and efficiency.

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